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# Analysis of Demand Response in the Smart Home Pilot

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**ABSTRACT:**
Flexibility is needed in the energy system as the share of renewable energy sources increases, creating a potential imbalance between supply and demand of electrical energy. There is also a need to increase energy efficiency and awareness among energy consumers. Demand response is considered as a concept to mitigate the risks associated with imbalance between supply and demand. For electricity consumers, demand response can provide savings on energy costs and promote awareness of energy efficiency. For utilities and system owners, demand response has the potential to smooth the imbalance between supply and demand and reduce the associated risks and challenges. This master's thesis is done for Vaasan Sähkö, energy company based in Vaasa. The focus of this study is on demand response in the residential sector and its potential benefits for both electricity consumers and utilities. The aim of the study is to analyse measured energy data from smart home pilot sites to investigate the performance of spot price-based optimisation in minimising electricity costs for customers. This is done in two tasks, by examining optimised load operating hours at optimal spot prices, and by comparing optimised and non-optimised load profiles. Heating disaggregation is effective for households without hot water heaters. In these cases, heating hours are well matched to optimal spot prices. Sites using direct electric heating have widely varying results. The comparison of load profiles showed the effectiveness of optimisation in shifting load from evening to night hours. In addition, the results showed that, on average, electricity is consumed in the pilot when the price is lower than the monthly average. The results showed differences in total energy consumption between the optimised and non-optimised scenarios, with overall higher consumption in the optimised pilot year. However, without detailed information on household characteristics, it is not possible to explain these differences in this study. Challenges to the study include a lack of detailed household metadata and characteristics, large variations in energy consumption between scenarios, and low numbers of measures in some locations, making it difficult to generalise the results.

**KEYWORDS:** smart home, demand response, optimisation

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| **VAASAN YLIOPISTO** | |
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**TIIVISTELMÄ:**

Sähköjärjestelmät ovat murroksessa, kun pyritään vähentämään kasvihuonepäästöjä. Uusiutuvien energialähteiden osuuden kasvaessa energiantuotannossa tarvitaan joustavuutta energiajärjestelmiin tasoittamaan tuotannon ja kulutuksen välisiä vaihteluita. Lisäksi tavoitellaan energiatehokkuuden ja -tietoisuuden lisäämistä kuluttajien keskuudessa. Kulutuksen kysyntäjoustoa on esitetty ratkaisuna sähköenergian tuotannon ja kulutuksen välisiin eroihin ja niistä aiheutuviin riskeihin ja haasteisiin. Kysyntäjousto voi tuoda säästöjä kuluttajien energiakustannuksiin ja samalla lisätä heidän tietoisuuttaan energiankulutuksesta. Energiayhtiöt ja verkonhaltijat puolestaan voivat hyötyä kysyntäjouston mahdollistamasta kulutuksen tasaisemmasta jakautumisesta, joka vähentää samalla epätasaisen tuotannon aiheuttamia haasteita.

Tämä tutkimus on tehty Vaasan Sähkö Oy:lle, joka on vaasalainen energiayhtiö. Tutkimuksen aiheena on pientalojen kysyntäjousto ja sen hyödyt sekä kuluttajille että energiayhtiöille. Tutkimuksessa tarkastellaan älykotipilotin mittausdataa, jossa asiakkaiden kuormia on ohjattu spot-optimoinnin avulla. Optimoinnin tarkoituksena on minimoida sähkönkulutuskustannuksia ylläpitäen samalla asumismukavuus. Tutkimuksen tavoitteena on arvioida optimoinnin suoriutumista vertaamalla kuormien käyttötunteja optimaalisiin spot-hintoihin sekä vertaamalla optimoitua ja optimoimatonta kulutusprofiilia, jotta voidaan tutkia optimoinnin vaikutuksia kohteissa.

Tutkimuksen mukaan kuormien erottelu toimii hyvin kohteissa, joissa ei ole lämminvesivaraajaa, ja näissä kohteissa lämmityksen käyttötunnit osuvat hyvin optimaalisten spot-hintojen tunteihin. Sen sijaan kohteissa, joissa lämmitysmuotona on suora sähkölämmitys, tulokset vaihtelevat. Kulutusprofiilien välisen vertailun perusteella optimoinnin voi todeta suoriutuneen hyvin, siten että se on siirtänyt kuormaa iltatunneilta yöaikaan. Lisäksi tulokset osoittivat, että pilotissa kulutetaan sähköä keskimäärin silloin, kun sähkön spot-hinta on alhaisempi kuin kuukausikeskiarvo. Tuloksista ilmenee eroja kokonaisenergian kulutuksen määrässä optimoidun ja optimoimattoman kuormaprofiilin välillä, mikä johtuu osittain tutkittujen vuosien välisistä eroista. Energiakulutuksen eroa, joka on keskimäärin suurempi optimoimattomassa profiilissa, ei kyetä tässä tutkimuksessa perustelemaan puutteellisten metatietojen vuoksi. Tutkimuksen haasteina ovat metatietojen puute kotitalouksista ja rakennuksista, suuret vaihtelut kulutetussa energiassa sekä pieni mittauskoko joissain kohteissa. Tämä vaikeuttaa tulosten yleistämistä.


**KEYWORDS:** smart home, demand response, optimisation

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## Abbreviations

| | |
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| CPP | Critical Peak Pricing |
| DER | Distributed Energy Resource |
| DSO | Distribution System Operator |
| HDD | Heating Degree Day |
| HEMS | Home Energy management System |
| ILM | Intrusive Load Monitoring |
| NILM | Non-Intrusive Load Monitoring |
| RTP | Real Time Pricing |
| TSO | Transmission System Operators |
| ToU | Time of Use |

# 1 Introduction

This master's thesis is done for Vaasan Sähkö. Vaasan Sähkö is an energy company based in Vaasa, Finland, providing electricity and energy solutions. Its main activities are electricity trading throughout Finland, the sale of district heating in Vaasa and electricity transmission through its subsidiary. In this chapter, the background of the thesis in terms of perspective, scope and motivation, as well as the structure of the thesis is presented.

## 1.1 Background

An increasing number of countries have announced long term goals to achieve net zero greenhouse gas emissions over the coming decades. According to IEA (2021), two-thirds of total energy supply in the energy sector is based on renewable energy in 2050. EU Commission published the emission reduction target in 2020, according to which the 2030 targets for renewable energy and energy efficiency should be further increased compared to previous targets (Ministry of Economic Affairs and Employment of Finland, 2022). In addition, there is a need to take care of the functionality of the electricity system with the increase of fluctuating renewable production. The Energy Efficiency First principle adopted by EU in 2016, highlights energy demand cost-effectiveness measures such as energy end-use savings or demand flexibility solutions, in addition promoting the small-scale production (prosumer) enabling citizens' opportunities to produce part of the consumed energy themselves and to participate in the energy market. The intermittent nature of renewable energy sources creates an imbalance between supply and demand, which can cause fluctuations in electricity spot prices. The fluctuating spot price on the wholesale electricity market harms the consumer as well as the energy company.

García-Garre et al. (2018) highlights the potential of improving customer flexibility to manage with this unpredictability of resources, as well as Balázs et al (2021) argue that it and residential prosumers as a potential source of flexibility for system operators. According to Shakeri et al (2020) smart meters can provide demand load management with the home energy management systems by enabling to schedule power consumption optimally based on energy prices, benefitting for both utility company and consumer sides.

## 1.2 Scope of Thesis

This study focuses on issues related to demand response in the residential houses. For electricity consumers, demand response can provide savings on energy costs and promote awareness of energy efficiency. For energy utilities and system owners, small-scale demand response, if scaled up, has the potential to smooth the imbalance between supply and demand and reduce related risks and challenges. However, energy transition in general requires new business models and technologies to enable it, as well as research and practical commercialisation cases, and this thesis is part of that development.

The aim of the thesis is to analyse the measured customer data from the smart home pilot sites. The thesis focuses on two main research questions as follows:

- Research Question 1 (RQ1): how the optimisation has performed when the target of the optimisation was the lowest electricity price for the customer (smart home pilot site)?
    - Task 1.1: At first the performance of certain optimised customer loads (appliances consumption) at a smart home is estimated.
    - Task 1.2: After that, the aim is to find out how smart home pilot sites' optimised profile has performed when compared to non-optimised customers.
- Research Question 2 (RQ2): In addition, the effect of different smart home pilot loads on the customer's load profile is investigated in order to find out whether a certain load is suitable as an optimised load or not.

## 1.3 Structure

Chapter 2 presents a literature review on future power systems, in particular regarding utilities and residential customers. A literature review of smart homes in future energy systems is presented in Chapter 3. The case study is presented in Chapter 4, in addition to the literature related to the study and its data. The methodology is presented in chapter 5. The results are presented in chapter 6, where subchapter 6.1. focuses on task 1.1 (see Section 1.2) and subchapter 6.2 on Task 1.2 (Section 1.2), while subchapter 6.3 reviews six examples that present different cases. Finally, Chapter 7 presents the discussions and Chapter 8 concludes the thesis.

# 2 Literature Review on Future Power System

In the literature, several smart grid initiatives referred to a modern grid, or grid modernisation. In general, the smart grid is considered an advanced power system using modern digital communication and information technology to monitor, control, and optimize the generation, distribution, and consumption of electricity. It integrates renewable energy sources, energy storage, and electric vehicles into the grid, enabling bidirectional flow of electricity and information between the utility and consumers. The smart grid aims to improve the efficiency, reliability, resiliency, security and sustainability of the power system while providing consumers with more choices, control, and flexibility in managing their energy consumption and costs (Liu et al. 2016). The EU (2023) defines the smart grid as energy networks that can automatically monitor energy flows and adjust to changes in energy supply and demand accordingly. When coupled with smart metering systems, smart grids reach consumers and suppliers by providing information on real-time consumption. In this chapter themes related to residential customer and energy utilities developing role in future power systems are presented.

## 2.1 Smart Grid

According to Liu et al. (2016), the goal of the smart grid is to improve the management and delivery of energy in a more effective and efficient way. The utility's role has evolved into a solution provider, and consultant for communications, data collection and management, and service provision among others. A smart metering system can provide several services for residential energy end, such as consumption data monitoring and management, helping customers to understand and manage their energy services. Moreover, smart metering enables new business models and services related to new relationship between customer and energy utility, where customers can contribute to the demand response, remote load management and microgeneration programs. They describe the demand response as a concept where during periods of high usage, resulting in high energy prices, end users reduce their usage and are rewarded for that reduction with lower energy price.

García Vera et al. (2019) claims that integrating these systems can be done in decentralised way by using microgrid systems. In this way there will be a possibility to exchange information between the consumers and the distributed generation centres. Also, it will be then evident that they need to be managed optimally. The integration of these systems can be carried out in a distributed manner via microgrid systems; this provides a set of technological solutions that allows information exchange between the consumers and the distributed generation centres, which implies that they need to be managed optimally. It is difficult to predict the amount of electricity that photovoltaic and wind turbines will be able to produce, as it depends on the availability of wind and sunshine at any given time. Because of this it is even more important to keep the balance between the supply and demand in microgrids to ensure stability while the intermittent distributed sources may vary notably. In a microgrid, according to García Vera et al. (2019), maintaining the balance between the power supply and demand is essential for stability. This is because the generation of intermittent distributed sources, such as photovoltaic and wind turbines, is difficult to predict, and their output may fluctuate significantly depending on the availability of primary sources like solar irradiation and wind speed.

## 2.2 Electricity Markets

Since currently it is not economical to store large amounts of electrical energy, energy must be produced at the same time as it is consumed (Kirschen et al., 2004). Electricity trade therefore refers to a certain amount of energy to be delivered during a specified period, has been typically an hour, but is switching to 15 minutes timeslots (Fingrid, 2024b). Since electrical energy delivered during one period is not the same commodity as electrical energy delivered during another period, the price is usually different for each period. Due changes in demand, production adjustments, must be made in the shorter basis to keep the system in balance. Such adjustments are considered as ancillary services, since they are services rather than commodities (Kirschen et al., 2004). The day-ahead market will switch to a 15-minute market time unit in 2025, by which time EU countries should have implemented a 15-minute imbalance settlement period (Fingrid, 2024b), and the Nordic intraday market will move to a 15-minute market time unit already in 2024. A shorter settlement period improves the accuracy of forecasts and enables the power balance to be controlled more effectively. Consequently, market prices will drive the balance between production and consumption, and the system will be closer to becoming a real-time electricity market.

Kirschen et al. (2004) concluded that commodities such as electricity often experience imbalances between agreed quantities and actual demand or production. They found that a regulated spot market that facilitates load balancing is critical to maintaining the reliability of the electricity system. This market, overseen by a system operator, operates on market-based principles, with participants offering energy at self-selected prices. As a spot market, it sets prices to resolve imbalances, but differs from a managed market in that bids and offers are selected by a third party rather than through bilateral agreements.

In Finland, the price of electric energy is determined on the wholesale market (Fingrid, 2023a). The Nord Pool Spot of the Nordic electricity exchange is owned by the Nordic grid companies, from Finland it is Fingrid Oyj. In practice, electricity buyers, such as industrial plants and retailers, set at what price and how much they want to buy electricity, and the sellers give their offers accordingly, whereby the price of electricity is determined at the intersection of supply and demand. In the Elspot market of the electricity exchange, the wholesale price of electricity is formed for each hour of the following day. However, the need for electricity may change, in which case electricity can be purchased from the intraday Elbas market, where the price of electricity often differs from the Elspot price. If the customer wants to ensure a certain price for electricity, a derivative contract can protect the price into the future for up to years. The price level of electricity producers' offers is affected by the electricity production method they offer, such as the variable costs of power plants. If the demand for electricity temporarily increases, more expensive methods are needed to produce electricity, which leads to an increase in price of electricity. Correspondingly, when demand is low, the price decreases (Fingrid, 2023a).

According to Liu et al. (2016), the smart grid presents the potential for enhanced coordination among market participants in near real-time, thereby expanding the pool of entities able to offer services within the electricity market. These capabilities hold promise for improving market efficiency, reducing costs, and are particularly significant in the context of transitioning to a decarbonized grid. One of the primary advantages is in the ability to empower demand to adapt flexibly to pricing signals. Generally, optimal outcomes are achieved when both consumers and producers base their decisions on prices reflecting the true marginal costs of their actions, alongside monitoring and enforcement of competitive market structures and behaviours, facilitated by the implementation of standards, taxes, and environmental policies.

Marginal cost of electricity varies across intraday and seasonal cycles, reflecting the patterns of demand. Therefore flat-rate pricing of electricity is inefficient. As alternatives, Liu et al., (2016) presented them as follow. A Time of Use tariff (ToU) reflects expected marginal cost and charges a higher rate for consumed electricity when demand is expected to be high. This directs the customer to use electricity, for example at night, with a timer. However, it can differ significantly from the actual marginal costs, and these tariffs cannot indicate specific times when demand and marginal cost are highest. Widely used with large industrial customers, the Critical Peak Pricing (CPP) contract allows the retailer to charge a high price for demand in specified hours. Customers are notified in advance of peak periods and given an opportunity to adjust their usage accordingly. Since CPP contacts limit the number of times they can be called, energy utilities may hesitate to use them, therefore CPP is less effective compared to time of use tariffs.

Real Time Pricing (RTP) exposes the customer to the wholesale price as it varies from settlement period to another. This ought to send the most accurate signals of the marginal cost of electricity, if the wholesale market is working well. The price will typically be published a day before, rather than the real-time market itself, so that customers have time to respond to it. Liu et al., (2016) stated real time pricing as more accurate prediction of the time-varying marginal cost of electricity than a ToU or CPP tariff. Wholesale prices are highly sensitive to the available production and transmission capabilities because energy must be produced when needed and cannot be stored on an industrial scale (European Commission, 2023).

## 2.3 Need for Flexibility

The system operator uses balancing, or flexibility, services in order to react quickly to unplanned fluctuations in demand or supply. The Nordic system has historically benefited from the availability of abundant hydro resources, while increasing amount of wind and other intermittent energy sources increase the need for additional system flexibility (Grigoryeva et al., 2018). As the integration between the Nordic and the continental system increases, the demand for the Nordic flexible resources will increase together with the need of an efficient transmission allocation.

Transmission System Operators (TSO) are facing the pressure that comes out of the necessity to maximise the flexibility (Grigoryeva et al., 2018). With network and generation expansion the flexibility can be ensured but also it will increase the demand-side response, storage technologies and electric vehicles. They claim that especially the demand-side response has not been fulfilled and tested with its full capacity. To exploit the capacity of the demand response steady market model is needed where the major and minor consumers would have an incentive to contribute to the flexibility of the system by providing services that would increase it. At the same time this would mean that the vast majority of the consumers would the use smart metering of their consumption so that the market could produce the attractive price signal.

According to Khajeh et al. (2022), when customers are active and use their smart households' intelligent devices for metering, they can eventually add to the flexibility and benefit financially from the effort. By being connected to the distribution networks they can offer the flexibility to TSOs and Distribution System Operators (DSOs) which can control the devices the way it is needed together with the system owners. This allows both the system operators and household customers to benefit from the gained flexibility and employ even more flexibility.

In the Balázs's et al. (2021) research it was underlined that even though conventionally, household have been seen as consumers that use and demand energy, they have their role in creating flexibility in building energy management. On the demand-side they can indeed create flexibility for the entire energy system. Especially residential prosumers can have a large effect on both DSOs and TSOs because they do use quite the share of the electricity that is produced but they are scattered with their location.

## 2.4 Data-Analysis

As the number of monitoring sources increases, manual analysis of raw data becomes unmanageable (Liu et al., 2016). Data analytics harnesses the potential of network data to provide automated decision support for utility engineers. Liu et al. (2016) describes that data analytics continuously processes online data using software algorithms to extract deeper insights, unlike basic analysis which typically yields one conclusion from past events. Smart grid-focused analytics platforms integrate diverse models tailored to customer needs, though delivering statistical model outputs to end-users poses challenges. Data science encompasses steps from data collection to visualization, employing techniques like data mining and machine learning to reveal patterns within raw data, ultimately aiding engineers in understanding trends through intuitive representations.

According to Liu et al., (2016), conveying statistical model outputs to end-users remains a significant hurdle. Data science produces algorithms that transform raw data into actionable insights, presented as reports or real-time alerts within analytics environments. Thus, they state that the data science process becomes a means of selecting the most appropriate algorithms for specific analytical tasks.

In a modern smart household a range of IoT sensors are collecting data (Chaganti et al., 2022). They argue that for these households the data-driven approach is considered to be most feasible since it uses the data collected from sensors. Völker et al. (2021) describes new possibilities for data collected from smart homes, arguing that it opens the possibilities for completely novel use cases. Most of the use cases are customised for the benefit of the power grid operator e.g. providing the ability to forecast and keep track of the energy consumption of the households or photovoltaic production or detecting some deviant consumption patterns. On the other side, the use cases for the consumer are still quite limited even though consumers can have an impact of their electrical energy consumption directly.

# 3 Literature Review on Smart Homes

According to IEA (2023) residential end users are consuming 27% of total energy consumption. During 2021, 82% of total energy consumed by Finnish households was used for heating space and domestic water (Statistics Finland, 2023a). In future power systems, smart homes will play an essential role in increasing the energy efficiency. In this chapter, some main features to enable smart grid functionality in residential homes are presented. Since in the pilot case, which is introduced in chapter 4, most heating systems are various electrical, first subchapter focuses on older heating systems while the subsequent chapters review more recent developments in residential energy management.

## 3.1 Heating Systems for Space and Domestic Water

Traditionally in Finland, electric heating has been popular for residential detached houses. In an electric heating house, a water heater is needed to store warm domestic water. In a house equipped with a centrally heated water circulation heating system, a heating water storage tank is needed, which can also function as a storage tank for domestic water. Generally, the water storage tank is heated with electric resistances. According to Motiva (2011), up to 30% of the total heating energy is used to heat domestic water in small residential houses. The resident's usage habits have a large impact on energy consumption, they estimate consumption to be 1500 kWh per inhabitant and the energy consumption of domestic water heating is distributed evenly over the year.

Residential households in cold regions typically rely on primary heating source, which can be district heating, direct electric heating, a heat pump, or oil heating (Sridhar et al., 2023). The primary heating method is predominantly utilised during cold months for space heating. In addition, households can increase their heating-related efficiency by installing an additional source of heating to complement their primary heating. The heating system can be partially reserving, reserving or direct (Ketola et al., 2017). Reserving capacity depends on the assembly method of the heating element, such as floor heating and the thickness of floor material. Electric heating can be implemented either room-specific or water-circulated (Motiva, 2011). Direct electric heating and radiators are the easiest and cheapest way to implement electric heating, however their main drawback can be high electricity price. The operation of the radiator is simple, its efficiency is high, and it can be adjusted precisely and quickly according to changes in the heating demand. Floor heating is a heating method which can be implemented as continuous or partially reserved heating, where the heat is stored in the floor material and concrete.

A central heating system, such as a central heating boiler and a water circulation heating system, is used to heat the entire building (Ketola et al., 2017). In a water circulation electric heating system, heat is stored usually in water and the heat is distributed to the rooms with a water-circulating distribution system (Motiva, 2011). Traditionally the heat generating device is either a water heater equipped with electric resistances or an electric boiler, however heat can be brought from several sources into the water tank. In reserving electric heating, both space heating energy and possible hot domestic water energy can be produced. A water boiler for domestic water can also be connected to the system. Oil heating is a building-specific heating method, where heating is implemented with the help of an oil boiler and a water-circulating heat distribution system (Ketola et al., 2017). In most households, electrically heated storage tanks are used to heat domestic water (Kipping & Trømborg, 2016). They describe that hot water-based central heating systems are relatively uncommon in most regions of Norway, typically being supplied by electric boilers or oil boilers.

Increasing number of various types of heat pumps are installed in residential houses in Finland. In heat pumps, energy is taken from the outside air, the ventilation of the house or the ground (Ketola et al., 2017). The heat pump transfers heat from one place to another within its operating values with high efficiency. During the winter in Finland, when the demand for heating is at its highest and the available heating energy is at its lowest, the air-water heat pump needs the additional energy of the electric resistance for heating or parallel heating system (Motiva, 2011). They consider an air heat pump to be suitable as a supplementary heating method for electric heating systems. According to Motiva (2011), while district heat is generally used in urban areas, also small houses can be connected to district heating network.

## 3.2 Optimisation and Forecasting of Energy Usage

As renewable energy poses a challenge to the whole power system, as the power system becomes more complex and creates instability because the sources renewable energy is generated from are unsteady. According to Lu et al. (2018), this makes optimal load scheduling more difficult, and this topic needs further studying. They add that the development of the smart grid also adds to the power system becoming increasingly complex.

In the research field of households' energy optimization, the energy management and Home Energy management System (HEMS) have become mainstream steadily (Ma et al., 2023). Both are considered as the reasonable energy-saving actions if there is a need of rational energy use or optimal costs. HEMS and energy management can be more reliable and efficient with exact short-term load forecasts. This will improve the ability to save energy and use energy efficiently.

## 3.3 Demand Response

Traditionally the electricity generation has primarily relied on large-scale power plants with adjustable output to meet demand fluctuations (Liu et al., 2016). However, the increasing integration of intermittent renewable energy sources poses a challenge for system operators in maintaining real-time supply-demand equilibrium. Distributed Energy Resources (DERs) offer the potential to inject power back into the grid from the customer side, although they are typically not under the ownership of system operators. This underscores the necessity for innovative approaches by system operators to achieve power system balance. Liu et al. (2016) describes demand Response (DR), as a concept where end-users curtail consumption during peak periods of high energy demand and cost, incentivized by lower prices during off-peak periods.

Demand Response systems typically aim to align electricity supply with consumption, prompting power utilities to adjust their production in response to demand fluctuations. However, this process can be costly, as it often involves importing additional energy, initiating or halting generating units, or implementing load shedding. Nevertheless, the emergence of the smart grid offers technological capabilities that enable power utilities to synchronize demand with generation. This is achieved with customer consent and through the implementation of time-based dynamic pricing, wherein unnecessary loads are curtailed, and energy consumption is shifted from peak periods to times of lower demand (Amer et al., 2021). Duman et al. (2021) states that at the household level, demand response initiatives by load-serving entities involve providing time-related pricing incentives or economic inducements to encourage end-users to engage in direct or indirect load control, facilitated by advanced metering infrastructure.

Balázs et al. (2021) explains that demand-side flexibility represents a valuable resource for system operators. However, due to the unpredictable nature of residential prosumers' schedules, it is challenging to establish a fixed quantity of available flexibility, which instead requires predictive forecasting. As stated by Khajeh et al. (2022), demand-side flexibility can be utilized by both DSOs and TSOs. In this scenario, residential consumers or prosumers respond to the flexibility requirements of the system operators. These requirements may be communicated in the form of prices or other incentives. Furthermore, aggregated consumers and prosumers can participate in various TSO-organized reserve markets, adjusting their consumption and production of DERs based on frequencies or other signals provided by the TSO.

Demand Response is not only for the benefit for the consumers to manage their electricity expenses and bills but also in improving the efficiency of the electricity market (Alotaibi et al., 2020). Further, for the future of the energy sector DR is very promising as a technology and in economic sense. According to Kirkerud et al. (2021) space heating in households and tertiary sector as well as heated water in households will be major sources of DR flexibility in the Nordics. Sridhar et al. (2023) describes that the flexibility provided by individual houses is relatively low but combined cumulative effect can provide significant support to the energy system during peak hours.

## 3.4 Home Energy Management System and Smart Metering

Overall, it seems that HEMS could be promising to achieve the balance between managing energy consumption and generation of power, as well as improve the operation of power system provided by power utility companies (Liu et al., 2016). HEMS are usually supported by various visualisation features and HEMS allows the management of different devices and appliances in households.  Modern households that can also be producers would particularly benefit from HEMS since HEMS enables automatic monitoring of energy consumption and cooperation with external services and producers. This kind of collaboration could contribute to a mutually benefiting business model for both parties.

HEMS offers the opportunity to customise the rational use of energy accordingly to the needs of the household residents (Liu et al., 2016). By functioning together with other services on a one single platform in households, energy management has the modern feel where choices are made by the residents' individual preferences taking into account the tariff for TOU (time of use) and price DR. It is also known that the comfortable temperature in the household is more prioritised than the electricity consumption. However, it can be considered that HEMS can even improve the quality of life.

Darby (2016) suggests that smart metering systems represent a pivotal aspect of the smart grid, offering significant benefits to both consumers and producers. For consumers, these systems afford access to a real-time and precise consumption data, facilitating improved service management and a deeper understanding of tariffs, suppliers, and individual consumption patterns. Moreover, smart meters foster a novel relationship between consumers and energy utilities, empowering consumers to participate in demand response initiatives, remote load management, and microgeneration programs through two-way communication channels that enable automatic data collection and real-time sharing via online portals, in-home displays, or mobile applications.

Furthermore, Darby (2016) highlights that smart metering fosters energy awareness among consumers, motivating them to enact changes to reduce energy usage and providing insights into the impact of their actions. Enhanced consumer education can occur through informative seasonal home energy reports encompassing consumption and billing data, alongside digital media dissemination, such as smartphones or in-home displays, featuring consumption graphs and historical reports with alerts for abnormal usage patterns. However, the efficacy of smart meters in driving demand response may be limited in households with low consumption levels or constrained by factors like housing conditions and users' technological literacy (Darby, 2016). In addition, while smart meters offer potential economic and social benefits, these may be limited compared to the benefits of investing in home insulation to reduce heating or cooling loads.

# 4 Case Study

This research uses as case study Vaasan Sähkö OY and Comsel System Ltd pilot project for their customers. The aim of the pilot is to improve the use of energy and the creation of new services (Comsel System Ltd, 2020). The solution uses smart metering to control the energy use while at the same time energy awareness is increased, in addition they claim that just by increasing the awareness, a 5-10% saving in energy costs is achieved. The optimization of the energy usage is carried out in a holistic way, learning from whole home consumption and in accordance with control possibilities and needs. The smart metering solution utilizes real-time consumption data, energy price data, weather data and forecasts. The aim is to heat the house and domestic water when the price of energy is low and keep the indoor temperature constant while maintaining a comfort level.

## 4.1 Pilot Customers and Data

In the pilot, the customer has a suitable electricity meter, or a smart measuring module connected to the meter (Comsel System Ltd, 2020). They communicate wirelessly with other installed devices such as internal temperature sensors and relays controlling the devices to be optimized. All sites in pilot are in or near Vaasa. To simplify the work, the sites from pilot with electrical vehicle charging and photovoltaic production were left out, and 48 sites were included in this study. Table 1 below presents house types and their optimised loads including heating methods, as well as possible water heaters and other additional loads. One site has as an oil burner, the office site has servers, and some cases have additional loads such as garages or sauna buildings which affect to the total load. The heating system method of a large water boiler is termed energy storage. It is noteworthy that the heating is not controlled in 9 sites.

The aim of the optimisation in the pilot is to control the loads so that the total costs are affordable for the customer. The optimisation considers the hourly day-ahead spot price, transfer fees, taxes and contract type while maintaining living comfort. However, in this study hourly spot hour is used to with all cases, since the data does not include what kind of contracts customers have.

**Table 1.** Smart home sites in pilot included in the study and their controlled loads.

| Heating method | House type | Total Quantity | Heating Uncontrolled | Without water heater | Oil Burner | Additional load |
|---|---|---|---|---|---|---|
| Direct electric | Detached house | 36 | 7 | | | 2 |
| Direct electric water heater | Detached house | 3 | 1 | | 1 | |
| Energy storage | Detached house | 4 | | 2 | | |
| Heatpump | Detached house | 2 | | 1 | | 1 |
| Direct electric | Townhouse | 2 | 1 | | | |
| District heating | Office | 1 | | 1 | | 1 |

The measured data to be analysed consists of hourly energy readings from the site meter. Energy measurements from 2021 are from the smart home pilot and are used as an optimised scenario. Corresponding energy readings from 2018 are used as a non-optimised scenario, assuming what the site's load profile would be without the optimisation. Hourly spot electricity prices of 2021 and 2022 are used to verify how the optimisation has performed, as presented in chapter 5. Chapter 4.2. presents an overview of the spot data. The study uses the Finnish Meteorological Institute's temperature measurements for Vaasa in 2021 (FMI, 2024a), which are used to create a model for disaggregating the heating load, as described in Chapter 5.

It is worth noting that there is no information on how loads have been or are allowed to be on, which has an impact on the analysis. In detail this means that spot optimisation allows the appliance to be on for a certain time, i.e. the relay controlling the appliance is on. The measurement data only contains the energy reading from the main electricity meter, there is no control information from the relay or the device, and no device level energy consumed. In addition, the available metadata is shown in Table 1, describing the different heating systems and other loads of the sites. There is no detailed or prior information on appliances, such as power rating. The pilot started in 2021, so many sites are missing data from the beginning of the year, which means missing data from the cold heating season. The general characteristic of the data is hourly measurement, which can be considered as a very low sampling rate (Zhao et al., 2020).

## 4.2 Overview on Spot Data

In this study, the hourly spot price of the years 2021 and 2022 is used. The 2021 spot prices are used to evaluate how the optimised loads during the 2021 pilot have been on compared to the optimal, cheaper hours. In addition, spot prices are used to create load profile scenarios as described later in chapter 5. The spot prices of 2022 are used to investigate the performance of the load profiles under more volatile price conditions. Figure 1 below presents the difference between the rolling average of spot prices in 2021 and 2022, as well as the difference between prices on weekdays and weekends. In 2022, the profile for weekends and weekdays is quite similar, unlike in 2021, where they differ significantly in the morning and afternoon hours. In particular, the average spot prices during the weekend morning and noon in 2021 are significantly lower than the evening values.

Figure 1 highlights that the lowest average spot prices occur during the night hours, making hours 0 to 5 optimal for optimised loads. However, spot prices can fluctuate considerably due to supply and demand dynamics. The highest averages occur during morning and early evening hours, with spot prices declining in the late evening hours. Weekend spot prices in 2021 offer longer optimal hourly periods, as morning hourly values are lower compared to weekdays.

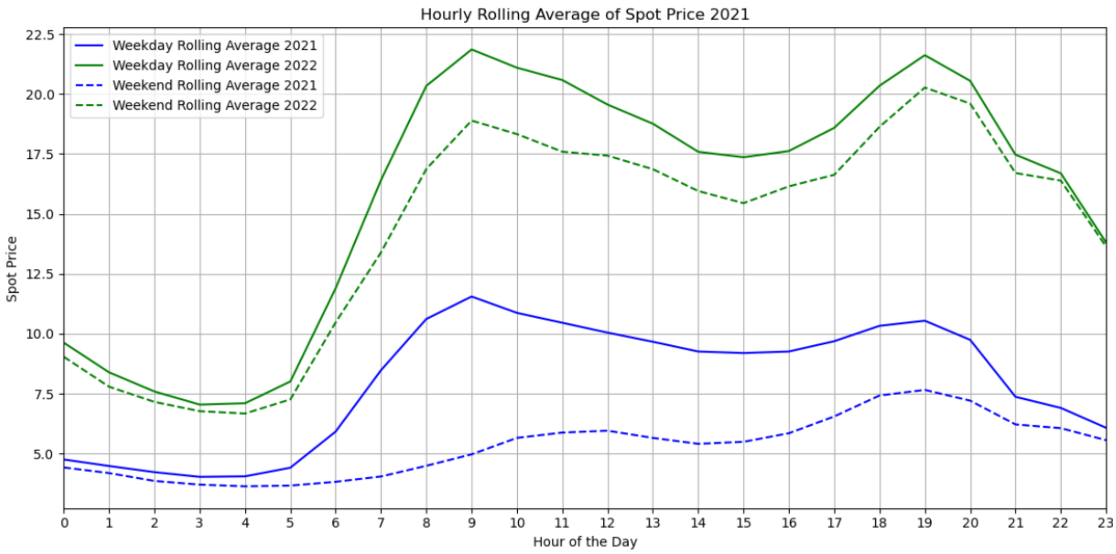


**Figure 1.** Rolling average of spot hours of 2021 and 2022

Hourly spot prices of 2022 tend to be higher and with larger distribution (Figure 3). However, some hours of 2021 have abnormal high prices compared to their normal distribution (Figure 2). The average and median values of the spot price are at highest in the morning and in the evening, while the small hours have the lowest values. Especially in 2022 the difference between evening and night, or rather difference between night and morning hours, is significant.

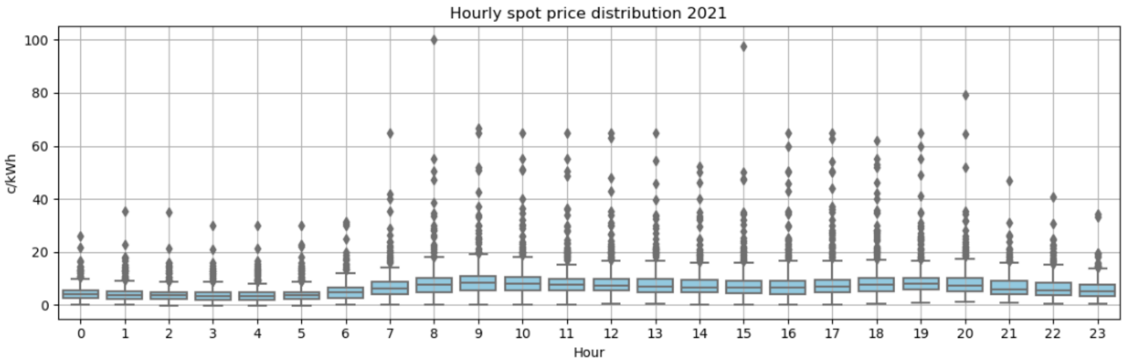


**Figure 2.** Hourly distribution of spot price in 2021.

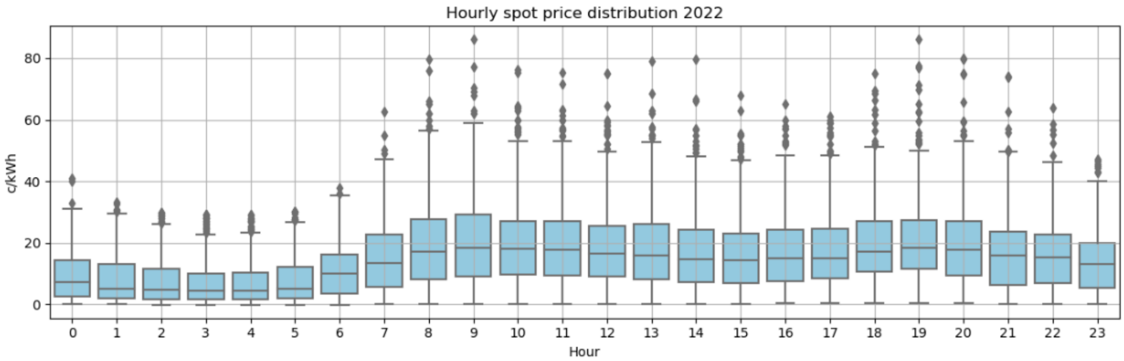


**Figure 3.** Hourly distribution of spot price in 2022.

## 4.3 Similar Studies

In this research comparable other studies, related energy consumption analysis or demand response of households, have been reviewed. In the study of Norwegian residential electricity demand, it was stated that electricity usage for estimated cases varies from year to year (Dalen & Larsen, 2015). Also, the temperature-corrected share of electricity consumption for heating varies between years. The temperature-corrected share of energy consumption was found rather stable for the years 1990, 2001 and 2006. In this case reasons for this were suggested e.g. the vast possibilities to substitute between energy types in Norwegian homes. It is difficult to avoid some everyday life routines like washing and heating and therefore they stay stable but over time it was found that the amount of electronic equipment has increased. Dalen & Larsen (2015) concluded that in their case there were no trends found in the use of electricity and other types of energy for heating.

The study of Hansen et al., (2022) points that the households energy demand's timing rather aligns with society's rhythms than individual household pattern. The vast impact comes from whether schools are open, the operating hours for different places, the working hours etc. Based on these societal timings, the households' activities determine the daily load pattern. Strong convergence between societal rhythms and daily load patterns of diverse types of households was described. They estimated that the impact of different characteristics of households on heating was rather low. From this point of view, it was suggested to focus on collective energy practices rather than on individual consumers because they cannot change the external factors of the larger society. The focus should shift from energy businesses making assumptions about consumers to a broader examination of people's activities and timing within their homes. Indeed, some variations may follow from the income level and job type of the individuals, but Hansen et al. (2022) concludes that there is really a little room for behavioural changes during the peaks of the energy consumption.

In their study, Lill & Pihlap (2022) conclude that it is not possible to compare different dates in different years if the days of the week are not taken into account. Consumption shares are different on weekends compared to other weekdays. Moreover, in their study Song et al. (2021), stated that the residential daily power consumption profiles of weekdays are different from that of weekends. According to Lill & Pihlap (2022), with daytime from 7 to 23 and nighttime from 23 to 07, it has been found that on Saturdays and Sundays the nighttime loads have been higher, while the daytime loads have been lower. This means that consumption can be separated in daytime and night-time periods. It is hard to compare the electricity price directly at the same time across different years because it is affected by many factors e.g. wind, solar, hydro etc energy production. These factors are varying all the time, but the share of electricity in the total daily price and electricity consumption can be compared. In their study the low and high-priced peaks were considered with the help of various types of hourly change in usage graphs. It was found that the usage corresponds to similar characteristics such as weekend, working day, season of the year and week.

Söder et al. (2018) argues that households in Nordic countries with a significant share of electric heating or heat pump usage have a significant potential to contribute to the flexibility of the energy system. In a study by Kurevska (2021) on heat pump optimisation, a base case scenario and alternative scenarios were compared. In comparison to the basic scenario, the biggest difference was observed when the load was shifted from coldest hours. However, even this adjustment did not lead to significant cost savings, in contrast to the base case scenario. This was because the coldest hours occur at night-time and the electricity price dynamics is not significant during nighttime. Kurevska (2021) concludes that this means that not much benefit was obtained from the load shifting.

Mata et al. (2020) found varying levels of potential flexibility in households' electricity load across countries, with Sweden having the smallest potential and Germany the largest, while energy-saving potentials also varied, indicating that simulation studies tended to identify more potential than demonstrative studies. In the study three different types of challenges were pointed out. One was related problems to financial problems such as unclear business models, unbeneficial market model and the high price of the smart metering. Second was technical challenges of the heat pump such as minimum running time, coefficient of performance correlation to indoor–outdoor temperature, as well as the fact that heating is season related. Third was relatively societal such as problems with individuals technical understanding or knowledge of pricing or the resistance to change the indoor temperature that they are accustomed to. In this study as an example of the flexibility measures there were mentioned different price mechanisms, user-oriented control strategies for heating, automated shifting of appliances' use, electronical vehicles charging algorithms, and consumer feedback.

In a Finnish study by Olkkonen et al. (2018), it was suggested that heating loads can bring a long-term technical possibility for the demand-side resource capacity in Finland in 2030. The demand-side capacity for heating fluctuates based on season and time of day, with higher availability during winter months in Finland due to weather conditions and peak demand. Heating and hot water storage systems, with potential shifting times of up to 12 hours, enable preheating to occur during off-peak hours, reducing strain on the grid during peak demand periods. However, individuals' preferences and their willingness to lose the comfort because of shifting time interval considered a limiting factor. In this study it was argued that the annual utilisation of demand-side resource capacity considerably decreases when the shifting time interval becomes more limited. Olkkonen et al. (2018) concludes that the use of demand-side resource capacity provides opportunities to balance the residual demand in the day-ahead market, reduce the operating hours of thermal power generation and reduce the need to import electricity during high demand periods. For wind power generation, it provides flexibility for better usability and efficiency in Finland for the non-peak hours.

In their study, Vesterberg & Krishnamurthy (2016) pointed that households' peak hours occur at morning hours 6-8 and coming back to home hours 18-21, and this is when the consumers use more energy, and it is more expensive during those times. The significant portion of energy usage happened in heating, lighting, and cooking. Even though this is rather understandable and not a surprise it has been a fact that households heat their homes when it is cold, use light when it is dark and cook before leaving the house and upon arrival at home. These functions add to the total load. Because these functions are so essential for living human beings it is not likely that they can be changed or shifted to be done at other times during the day. It is eminent that the price is not guiding the usage of the individuals in this case. The study estimated load curves of household. They used only subsample of the full data, and it composed of all working days in February as the coldest month in which heating devotes the highest load share. The data was only for detached households. Subsample data was also compared to June because it was considerate the warmest non-vacation month.

On the other hand, in study of Sridhar et al. (2023), it is recommended that the heating source should be identified before gathering the household consumption data. The data from a particular individual household is not that important as having a full combined data form vast number of households. This would help the formulation of sustainable electricity system during peak hours. This is important because it will affect the flexibility potential which can be exaggerated if for instance the primary heating system is mistaken to be electric based and the supplementary heating system to be non-electric based. The mistake comes from the fact that electric-based heating is used only during the coldest periods of the year and not throughout the whole period. The accuracy of the flexibility estimation highlights the significance of both power state estimation and electricity market needs, which are very crucial with the increasing share of renewable energy and the electrification of the heating sector. Using multiple different heating sources makes it harder for the approach to identify flexibility possibilities in Nordic countries. This approach is gaining more influence in a sustainable energy system dominated by intermittent renewable energy sources. Sridhar et al. (2023) states that the households heating system should be identified with the minimum data requirement and this is vital for the individual’s data usage and privacy.

## 4.4 Non-Intrusive Load Monitoring

Appliance load can be monitored to provide detailed energy metering and disaggregateed energy consumption information (Zoha et al., 2012). This improves the automated energy management systems and gives the ability to distinguish the high energy consuming devices. By knowing this, the automated energy management system can suggest energy saving strategies such as changing high power consuming operations to off-peak times. Zoha et al. (2012) describes Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM) as the two approaches to device load monitoring. Since ILM approaches require one or more sensors per appliance, they are referred to as distributed sensing methods. For NILM, a single meter is sufficient, so it is referred to as a single sensing method. The ILM method is more expensive to use, but it is also more accurate in measuring device specific energy consumption compared to NILM. ILM also requires multiple sensor configurations and is more complex to install. For this reason, they claim that NILM is more commonly used in large cases.

According to Zoha et al. (2012), appliance load monitoring research is more focused on NILM because of the high cost and intrusive nature of ILM methods. In the research NILM has brought promising results while the cost and complexity have been kept rather low. Estimating energy consumption can be considered as a non-intrusive appliance load monitoring issue (Song et al., 2021). Meanwhile, it can also be approached as an energy disaggregation task withing buildings. In their study, Song et al. (2021) proposed a reference-based change-point model for non-intrusive energy consumption estimation, highlighting its benefits such as independence from high sampling rate data or prior information of the appliance. They defined the base load to be the power consumption independent of the outdoor temperature, identifying heating process through gradients less than zero, and considering minimums as base load.

# 5 Methods

The effectiveness of the optimisation in smart home pilot is analysed using two approaches, first it analyses how the heating and hot water heater loads have been on compared to the optimal spot hours of the day. For this purpose, the loads are disaggregated from the measured data, which is explained in chapter 5.1. The daily mean and median value of the spot price is calculated, and either the median or mean daily spot price is used as a threshold to determine whether the load is operating during the optimal hour. Another approach is to compare optimized and non-optimized load profiles considering 2021 and 2022 spot prices as described in chapter 5.2.

## 5.1 Disaggregating Loads

The base load of the site considers the temperature-independent load, and the temperature-dependent load considers the heating load. The reference-based change point method and a piecewise linear regression model are utilized to estimate the base and heating loads. This is done by modelling the ratio of hourly energy measurements (y-axis) in terms of the corresponding temperature value (x-axis). The purpose is to determine the maximum and minimum energy value with a three-part regression model and to estimate the difference between them, which represents the maximum heating power. The maximum value is identified as the highest point of a linear line, while the minimum vale is determined as the point where the line starts to react to the temperature. As typical example in Figure 4, according to the light brown regression line, the basic load can be estimated at 0.9 kW and the maximum value at 6.2 kW. In this case, the maximum heating power can be estimated as 5.3 kW.

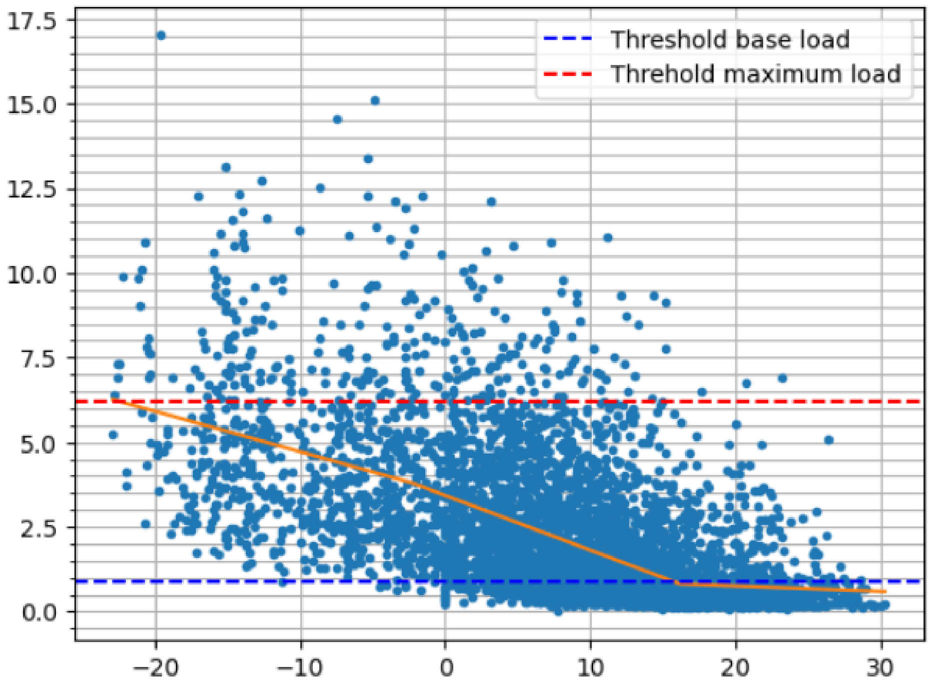


**Figure 4.** Example of heating load estimation based on energy measures and temperature.

Since the use of the water heater is independent of the temperature and can be considered the same throughout the year, it has proved difficult to disaggregate the water heater's energy from the measured data. In order to solve this problem, a method based on the experience of Vaasan Sähkö is used. The algorithm is defined on the assumption that the water heater is switched on during the "night electricity period", i.e. from 22:00 to 06:00. The total energy demand of the water heater is set to three times its nominal power. The nominal water heater rating for a given site is iterated based on the statistical mean + standard deviation of the August energy measurements (see Figure 5). This is based on the experience that August is not considered a holiday season in Finland and the daily routines that affect energy measures work normally, while on the other hand August can be considered a warm month when heating energy is not needed. Therefore, the energy peaks during the August night-time electricity hours can be assumed to be the load of the water heater.

```
count    279.000000
mean       1.541237
std        1.291465
min        0.188000
25%        0.537000
50%        1.071000
75%        2.214000
max        7.292000
Name: energy, dtype: float64
Water heater nominal rating: 1.5412365591397845 + 1.2914648678882175 = 3.0
```

**Figure 5.** The nominal water heater rating, here 3 kW, is defined from the August night energy measures, rounded to 0 decimal.

In order to maintain a stable indoor temperature and living comfort, it is assumed that the demand for heating power exceeds the water heater. The following determines which load could occur during certain hours:

Heating system is on if:

energy > heating power

Water heater is on if only one of following conditions is satisfied during 22 to 6:

1) energy > heating power + water heater rating
2) heating power > energy > water heater rating

In addition, the water heater is determined to be on for a maximum of three hours during the night electricity time, this is estimated as the energy needed to recharge the boiler. Figure 6 shows how the algorithm works on a sample day, 7.-8. December. True at certain hours means whether heating and/or water heater is on at those hours. The column "wh_cumulative" calculates the cumulative energy of the water heater and limits the hours to a maximum of three and resets after the night hour.

| datetime | energy | heating_on | water_heater_on | wh_cumulative |
|---|---|---|---|---|
| 2021-12-07 21:00:00 | 10.123 | True | False | 0 |
| 2021-12-07 22:00:00 | 10.933 | True | True | 3 |
| 2021-12-07 23:00:00 | 8.099 | True | False | 3 |
| 2021-12-08 00:00:00 | 6.896 | True | False | 3 |
| 2021-12-08 01:00:00 | 7.624 | True | False | 3 |
| 2021-12-08 02:00:00 | 2.593 | False | False | 3 |
| 2021-12-08 03:00:00 | 6.988 | True | False | 3 |
| 2021-12-08 04:00:00 | 9.836 | True | True | 6 |
| 2021-12-08 05:00:00 | 4.328 | False | True | 9 |
| 2021-12-08 06:00:00 | 7.796 | True | False | 9 |
| 2021-12-08 07:00:00 | 4.986 | False | False | 0 |

**Figure 6.** Example of how the algorithm works when the heating power is 5.3kW and the water heater is 3kW.

## 5.2 Comparing Load Profiles

The comparison between optimised and non-optimised profiles is made by combining hourly data from different years. Due to the differences in the patterns of spot price and energy consumption between weekdays and weekends, data from different years have been combined to match the weekdays. As the first day of 2022 (1 January) is a Saturday, data for other years are set to start on their first Saturday. Similarly, the last day of 2018 is a Monday and the last data for other years are also from their last Monday (see Figure 7). Energy measurements from 2018 represent the non-optimised scenario and energy measurements from 2021 represent the optimised scenario. All sites with measured energy data from 2018 are calculated. Hours with missing energy measurements were excluded from the comparison, so only those hours with a corresponding energy measurement from both the optimised and non-optimised scenarios are considered.

| | datetime18 | energy_2018 | spot_price_2022 | datetime22 | energy_2021 | datetime21 | spot_price_2021 |
|---|---|---|---|---|---|---|---|
| **0** | 2018-01-06 00:00:00+02:00 | 11.14 | 29.76 | 2022-01-01 00:00:00+02:00 | 11.136 | 2021-01-02 00:00:00+02:00 | 2.564 |
| **1** | 2018-01-06 01:00:00+02:00 | 8.71 | 46.60 | 2022-01-01 01:00:00+02:00 | 9.194 | 2021-01-02 01:00:00+02:00 | 2.559 |
| **2** | 2018-01-06 02:00:00+02:00 | 6.62 | 41.33 | 2022-01-01 02:00:00+02:00 | 7.739 | 2021-01-02 02:00:00+02:00 | 2.491 |
| **3** | 2018-01-06 03:00:00+02:00 | 6.33 | 42.18 | 2022-01-01 03:00:00+02:00 | 5.786 | 2021-01-02 03:00:00+02:00 | 2.474 |
| **4** | 2018-01-06 04:00:00+02:00 | 1.95 | 44.37 | 2022-01-01 04:00:00+02:00 | 2.135 | 2021-01-02 04:00:00+02:00 | 2.466 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **8636** | 2018-12-31 19:00:00+02:00 | 0.61 | 50.95 | 2022-12-26 19:00:00+02:00 | 1.843 | 2021-12-27 19:00:00+02:00 | 20.710 |
| **8637** | 2018-12-31 20:00:00+02:00 | 1.21 | 47.66 | 2022-12-26 20:00:00+02:00 | 1.600 | 2021-12-27 20:00:00+02:00 | 19.605 |
| **8638** | 2018-12-31 21:00:00+02:00 | 1.20 | 47.62 | 2022-12-26 21:00:00+02:00 | 0.762 | 2021-12-27 21:00:00+02:00 | 16.133 |
| **8639** | 2018-12-31 22:00:00+02:00 | 7.83 | 44.04 | 2022-12-26 22:00:00+02:00 | 1.921 | 2021-12-27 22:00:00+02:00 | 12.291 |
| **8640** | 2018-12-31 23:00:00+02:00 | 9.82 | 29.68 | 2022-12-26 23:00:00+02:00 | 4.876 | 2021-12-27 23:00:00+02:00 | 11.998 |

**Figure 7.** Data from different years are combined, the energy measures from 2018 and 2021 are from a specific site, the spot prices are from the years 2021 and 2022.

The comparison is made for each site by calculating the realised hourly costs based on the 2021 and 2022 spot prices and the hourly energy measurements of the optimised and non-optimised scenarios (Equation 1). The average of the realised costs for each hour is used for the comparison. By examining the difference in the realised costs in these scenarios, the impact of optimisation is assessed. The difference in these profiles shows how optimisation works from a demand response perspective. It is obvious that the realised cost profile is calculated in 2021 spot prices, as the optimisation takes place in 2021. However, by using the 2022 spot price in addition, the scenarios are examined with more varying spot prices.

$$Hourly\ Cost = Hourly\ Energy * Hourly\ Spot\ Price \qquad (1)$$

The ratio of the average realised costs of the optimised and non-optimised is calculated to identify the hours with a significant difference. The ratio for the realised hourly cost is calculated as the average of the realised hourly cost of the optimised divided by the non-optimised, the results are explained in detail in Chapter 6.2.2. The example in Figure 8 is the calculation of load profiles for a specific site in 2021 spot price. The continuous line, blue for optimised and red for non-optimised, represents the average of the realised hourly costs (cents per hour). The dashed line, blue for optimised and red for non-optimised, represents the average of the hourly energy measurement (kWh). Figure 8 shows the hourly averages of energy and cost, but it is also important to consider the hourly averages of spot hours and optimal spot hours, as shown in Figure 1 of Chapter 4.2. Overall, in this example in Figure 8, the optimised profile has higher realised cost values, but at 0 and especially at hours 22 and 23, the non-optimised profile is higher. For example, the ratio of hour 22 is 0.66 (23.9 kWh / 36.0 kWh).

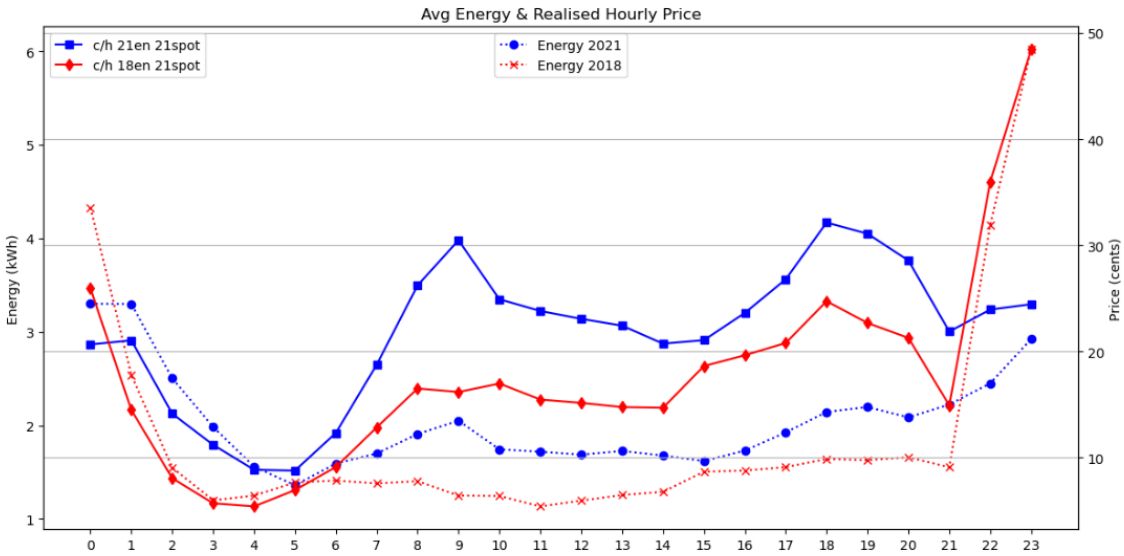


**Figure 8.** Example of certain sites hourly load and realized cost profile.

Furthermore, the load profiles of the optimised and non-optimised scenarios are compared on a monthly basis based on the average cost of energy consumed. The average monthly cost is calculated by dividing the sum of the hourly costs for the month by the sum of the hourly energy consumption for the month of site (Equation 2). The monthly load profile percentage (Month% in Equation 3) presents how energy is consumed on average when spot prices are cheaper. A negative value indicates that, on average, the profile consumed energy during cheaper hours than the monthly average of the spot price and positive values indicate the opposite. The averages of the monthly load profiles are calculated from all sites for both the optimised and the non-optimised scenarios.

$$Average\ Monthly\ Cost = \frac{\sum Hourly\ cost}{\sum Hourly\ Energy} \tag{2}$$

$$Month\% = \frac{Average\ Monthly\ Cost - Average\ \ Spot\ Price\ of\ Month}{Average\ Spot\ Price\ of\ Month} \quad (3)$$

# 6 Results

In order to answer the research question of how the optimisation has performed, it is firstly evaluated how the loads have been on during the optimal spot hours, and secondly how the optimised load profile compares to the non-optimised one. From the pilot case, 48 sites are included in the disaggregation analysis, of which 43 sites have measured energy data from the year 2018 and are included in the load profile comparison.

## 6.1 Task 1.1: Disaggregation of Optimised Loads

Loads are disaggregated from energy measures as described in Chapter 5. Based on energy measurements and disaggregated loads, load operating hours are defined and compared to whether those hours were at optimal spot prices. A total of 48 sites are included in the analysis, as shown in Table 1 in Chapter 4.

### 6.1.1 Heating

The daily median is used as a reference for optimal spot hour for heating, where there are 12 optimal and 12 non-optimal hours in a day. Statistics on the correlation between heating and optimal spot price for all sites having a water heater are presented in Table 2. The table present all sites in addition to sites divided into different categories, such as typical site, sites without a water heater and sites where the heating is classified as uncontrolled. The typical site column includes cases where the house type is a detached house, the heating method is direct electric, site has a water heater and no additional loads.

The method does not work for sites with an oil burner, because their energy-temperature regression curve decreases at low temperature, indicating that an oil burner is then used. Sites with low number of measurements, especially when cold dates are missing, have difficulty estimating the maximum heating output. In this case, the assumed heating power remain as low, which makes disaggregation challenging. In cases where the heating is not controlled, disaggregating the heating load is challenging because the method captures the maximum heating power, and not hours when the heating is only partially on.

**Table 2.** Statistic of heating operating hours when the spot price was below the daily median.

| Statistics of sites | All sites | Typical sites | Sites without water heater | Sites heating uncontrolled |
|---|---|---|---|---|
| Mean % | 62.0 % | 60.6 % | 78.3 % | 57.4 % |
| Min % | 40.9 % | 46.6 % | 72.1 % | 40.9 % |
| Max % | 83.8 % | 78.3 % | 83.8 % | 83.3 % |
| Median % | 61.2 % | 61.2 % | 78.9 % | 55.4 % |
| Number of sites | 48 | 27 | 4 | 9 |

Surprisingly, a certain site with uncontrollable direct electric heating has close to the best percentage (83.3%) of matching heating hours to the spot price below the daily median. This case is viewed in detail as sample 1 in chapter 6.3.1. In general, the disaggregation of heating worked in sites where there was no hot water storage tank, because the energy spikes are noticeable and can thus be interpreted as heating energy. Energy storage, heat pump and district heating were the heating methods for sites without a boiler for domestic water. The best results are over 80%, while the lowest significantly below 50%.

### 6.1.2 Water Heater

According to Vaasa Sähkö's experience, the typical power of a pilot customer's water heater is 3 kW connected to three phases, and a typical 1 kW heater is a single-phase device. The results of the iteration of water heater classifications are shown in Table 3. A power of 2 kW can either mean that a 3 kW heater is connected to 2 phases, or that the nominal power is 1.5...2 kW connected to 1 phase. Some of the 2 kW and 4 kW values can be explained as iteration error, as the actual rated value is likely to be 3 kW. The method has simplifications and limitations which are described in chapter 5.1, it is assumed that the water heater cannot be switched on during the day. Although this is the default setting, it does not take into account cases where the user has manually adjusted the water heater or where the customer has requested the water heater to be switched on outside the assumed night time electricity period. Furthermore, if the recharge requirement is defined as three hours at a nominal value, the method does not take into account whether the water heater needs more time to heat during the day if it is not filled at night. On the other hand, the recharge requirement tends to be fulfilled during the night hours and the method is not able to find the water heater's operating hours in the early morning hours.

**Table 3.** Iterated water heater ratings.

| Water heating rating (kW) | Quantity |
|---|---|
| 1 | 3 |
| 2 | 15 |
| 3 | 20 |
| 4 | 4 |
| 5 | 1 |
| 7 | 1 |

The hours of use of the water heater are shown in table 4 below. The hours of usage are compared to determine whether the water heater operation occurs when the spot price is below the daily mean. The daily mean is used as a reference for the optimal spot hours, as the spot prices during the assumed operating hours from 22 to 6 are typically the lowest of the day. Hours 22 and 23 are reviewed since, in addition to the mean spot price, the energy consumption is typically highest during these hours assumed operating hours. For reference, the last row represents the percentage of the spot price that fulfils the condition of below the average of daily the mean at that hour. The mean values are relatively close to the hourly reference percentage, however the weakest results are significantly low, indicating that the method is not valid in these cases.

**Table 4.** Statistics of the operating hours of the water heater when the spot price is lower than the daily mean at hours 22 and 23.

| Statistics of sites | Hour 22:00 | Hour 23:00 |
|---|---|---|
| Mean % | 52.4 % | 72.0 % |
| Min value % | 17.6 % | 25 % |
| Max value% | 71.4 % | 86.9 % |
| Median % | 52.3 % | 73.9 % |
| Number of Sites | 44 | 44 |
| % of Hours with Spot Price Below the Daily Mean | 58.1 % | 74.8 % |

## 6.2 Task 1.2: Comparing Load Profiles

The optimised scenario with 2021 energy data and the non-optimised scenario with 2018 energy data are compared using the spot price of 2021 and 2022. 43 sites have measured energy consumption data from 2018 and the scenarios are compared.

### 6.2.1 Overall Difference of Cumulative Total Cost and Energy

The cumulative sum of total energy and costs has been calculated using the 2021 and 2022 spot prices. Hourly energy measurement only considered if there is an energy reading for the corresponding hour in both 2021 and 2018. The statistics are presented in Table 5 below. The percentages are the results of the optimised scenarios compared to the non-optimised scenarios.

**Table 5.** Statistics for all sites comparing optimised and non-optimised scenarios, total energy and cost.

| Site Statistics | Total Energy 2021 vs 2018 | Total Cost Difference in 2021 Spot Prices | Total Cost Difference in 2022 Spot Prices |
|---|---|---|---|
| Mean % | 7.3 % | 11.9 % | 4.1 % |
| Min value % | -28.4 % | -31.0 % | -35.0 % |
| Max value % | 36.0 % | 47.0 % | 30.0 % |
| Median % | 6.8 % | 15.0 % | 4.8 % |
| Number of Sites | 43 | 43 | 43 |

As can be seen in the Total Energy 2021 vs. 2018 column (Table 5), the total energy sum is generally higher, however there are large variations, as the highest values are a 36% increase, while at the lowest there is a -28% decrease in the energy sum in the optimised scenario compared to the non-optimised scenario. The large variation in the difference in the total amount of energy is also reflected in the total costs, with the highest value for the difference in costs being as much as 47%. The difference in total energy between years can be explained by the higher demand for heating energy, but various factors that influence the energy demand of the household, such as changes in consumption or behavioural factors, or site characteristics, are not known, therefore the total energy difference cannot be explained within this study. However, as the main objective of optimisation is not to reduce energy consumption but to optimise consumption according to spot prices, it is appropriate to examine how the load profile has changed between the optimised and non-optimised cases, as described in the following subsections 6.2.2 and 6.2.3.

The results show that optimising with spot prices in 2022 gives a good result for total costs. This may be due to the spot price fluctuations in 2022 as described in chapter 4.2. These results, which compare scenarios at 2022 spot prices, can only be discussed if it is borne in mind that the actual spot optimisation of the controlled loads in the pilot takes place at 2021 prices. For this reason, it is not appropriate to examine the individual hourly costs, but the total hourly costs over the study period can be examined, which highlights the average difference in spot prices between 2021 and 2022.

### 6.2.2 Average Realised Hourly Cost

Averages of the realised hourly costs for each hour were calculated using corresponding spot data from the year 2021 and compared between the optimised and non-optimised load profiles. The heat map in Figure 9 shows the ratio of the average realised costs for each hour of the sites, so that the optimised is relative to the non-optimised. In the heatmap the columns represent the hour, and the row represents a site. Ratios greater than 1 indicate that in that hour the realised cost is higher in the optimised scenario and if it is less than 1, the realised cost is higher in the non-optimised scenario. A warm colour means that the cost for that hour is relatively higher for the optimised site, and a cold colour means the opposite. The heatmap illustrates the difference in realised costs described in Figure 8 (Chapter 5.2). For example, the case mentioned is located on row index 41 in the heatmap.

In general, the realised costs are shifted from hours 22 and 23 to the night hours 1 to 5. This can be seen as the desired outcome of optimisation, considering the average of spot prices and optimal spot hours (Figure 1 of Chapter 4.2.). In most cases, the value of hours 22 and 23 is less than 1 and the block is bluish, whereas the night hours show higher values with reddish colours. In other words, the overall difference in load profiles can be detected. There are several cases where the ratio at hour 7 is significantly high. Overall, this may be due to the fact that some optimised loads, such as the water heater, were more active in the morning hours. Due to the lack of a valid disaggregation method for the water heater, this cannot be verified. However, the ratio values do not necessarily explain how the optimisation has worked, as in some cases the total energy demand is significantly higher in the optimised scenario. Certain cases are examined in detail in chapter 6.3.

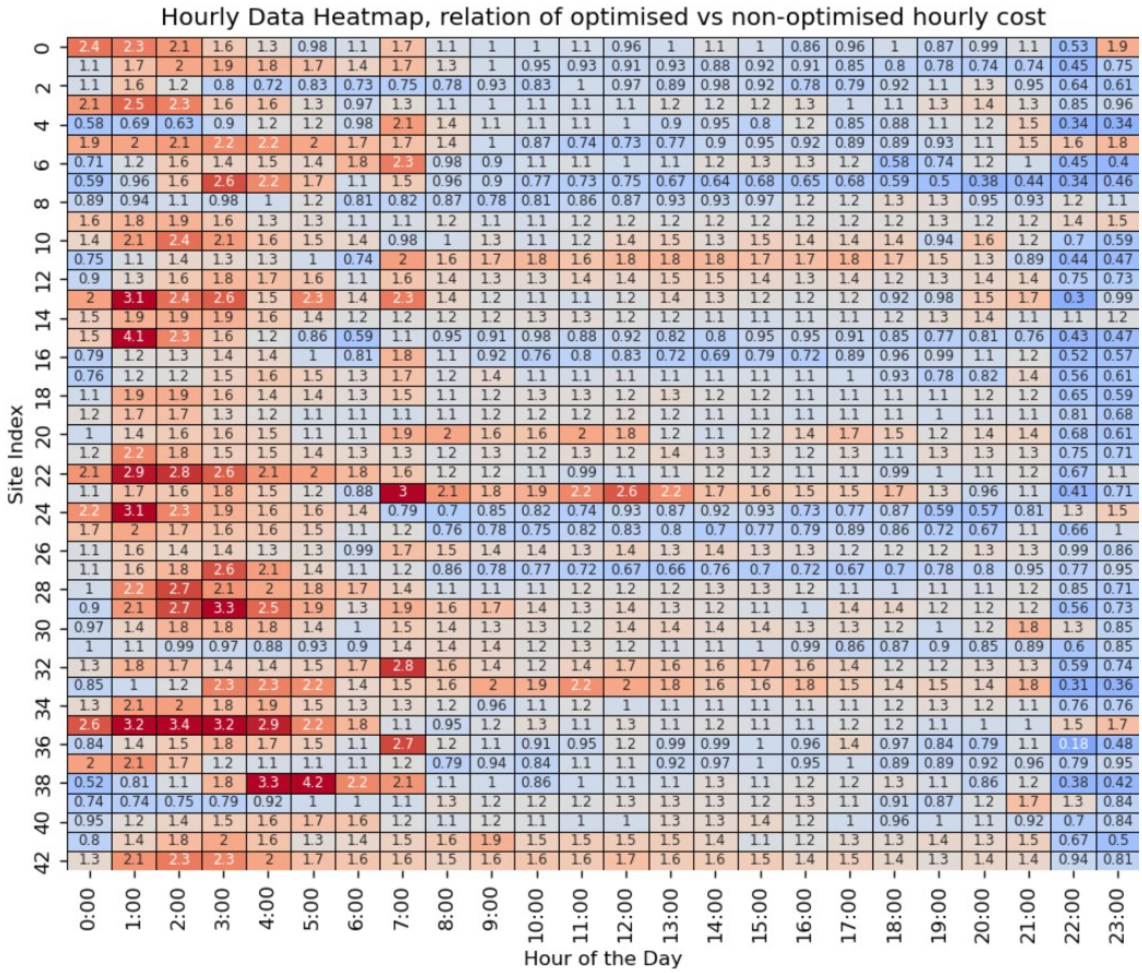


**Figure 9.** Relation of optimised (2021) and non-optimised (2018) average of hourly cost based on 2021 spot price.

A correlation matrix in Figure 10 presents the correlation of costs across hours from the heatmap (Figure 9). A relatively high negative correlation between the costs of hours 7 and 22 may be due to cases where the ratio is significantly high in hour 7 and correspondingly low in 22. In addition, the correlation matrix highlights the phenomenon that hours 8 to 21 are different from night hours: day hours are correlated with each other, while late evening and night hours are more correlated with their adjacent hours. A particularly sharp boundary of non-correlation is between hours 6 and 7 in addition to 21 and 22. This can be interpreted as the non-optimised scenarios operate on the night power principle (hour 22 to 6), where controlled loads are set to operate from hour 22, and the optimisation has mitigated this operation.

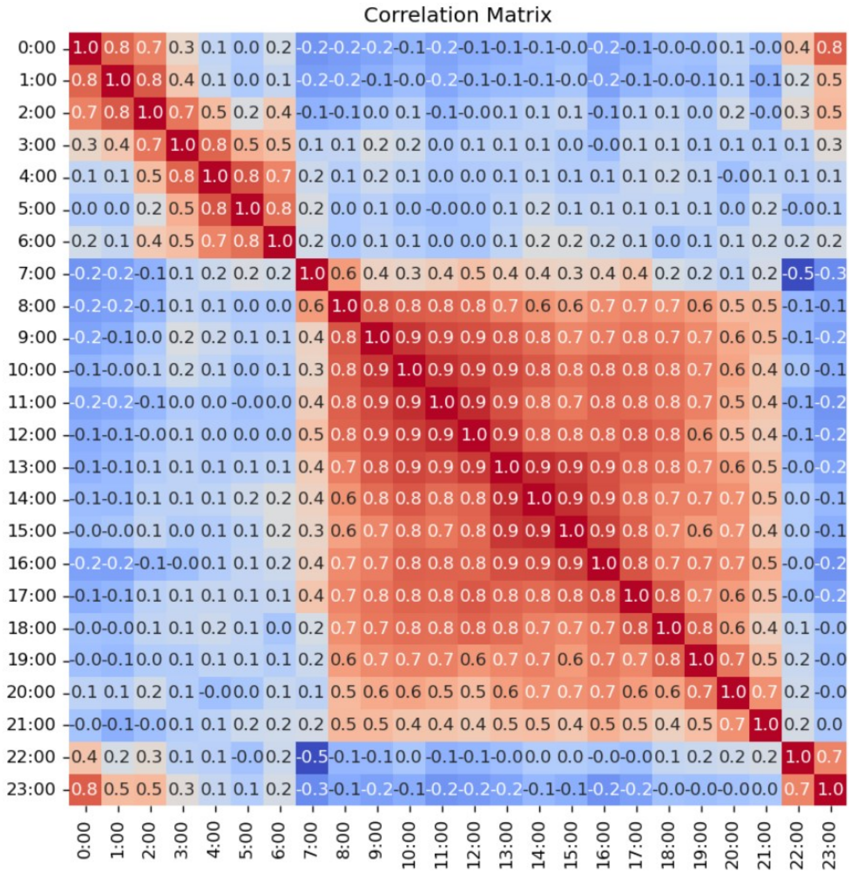


**Figure 10.** Correlation between hourly average relation of realised costs. Based on Figure 9 and-spot price of 2021.

### 6.2.3 Monthly Load Profile Comparison

Based on the average cost of energy consumed, the load profiles of the optimised and non-optimised scenarios are compared on a monthly basis, as described in Chapter 5.2. A negative value indicates that, on average, the profile consumes energy during hours that are cheaper than the monthly average spot price, while positive values indicate that energy is consumed during expensive hours.

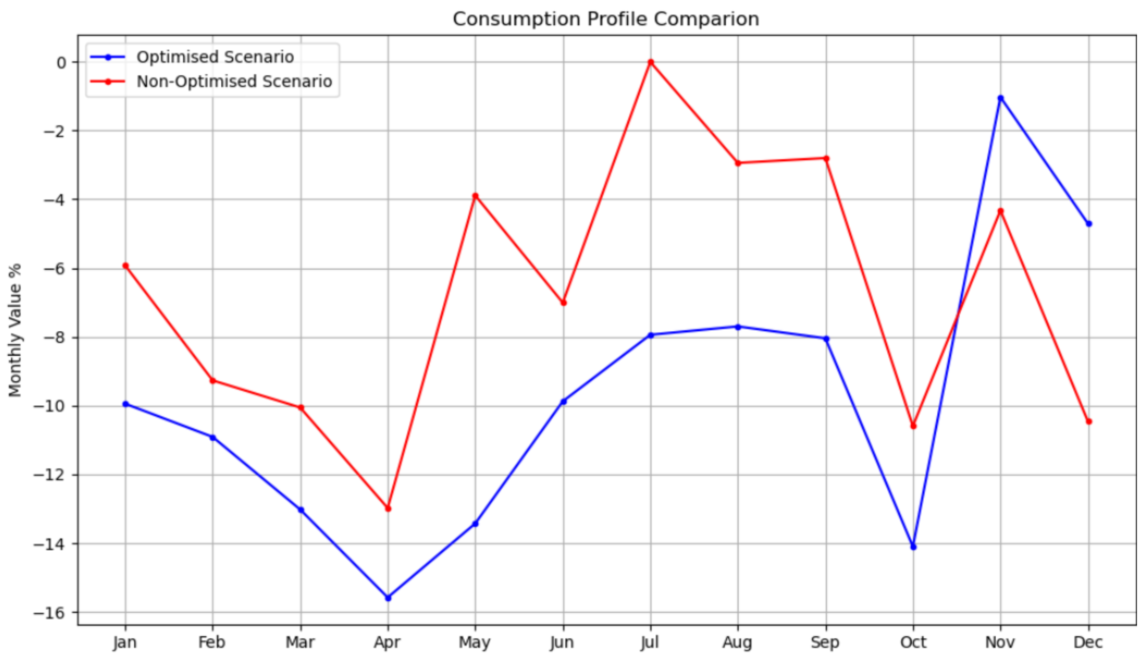


**Figure 11.** Monthly scenario comparison of all sites.

The monthly percentage value represents the average amount of energy consumed when the spot price is below the monthly average (Figure 11). In general, the profiles have a negative value, indicating that electricity is used when the price is below average. The optimised scenario has slightly lower values compared to the non-optimised, but in November and December the non-optimised profiles are more successful. It is worth noting that due to the lack of energy readings from the first half of the year, there are significantly fewer values considered for the period from January to May. A different curve in November-December may be due to a higher demand for heating energy. The relatively good overall values for non-optimised profiles may be explained by the fact that energy consumption at many sites follows the night-time electricity routine, where heating and/or hot water are set to operate during the late evening and night hours. These hours are typically the cheapest spot hours of the day.

## 6.3 Sample Sites

In this section, different cases are presented that show the different load profiles and the results of the optimisation at hours 22, 23 and in some cases at hours 7, 19 or 20. Hours 22 and 23, and in some cases hour 7, are examined because their cost ratio values on the heat map (Figure 9) are noteworthy. In example 4, hour 20 and in example 5, hour 19 are chosen as special cases for examination. In examples 1 and 2, the total energy was similar between the optimised and non-optimised scenarios. Samples 3 and 4 are cases where the total energy has increased significantly in the optimised scenario. Sample 5 is a case with an energy storage as heating method without a water heater as load. Sample 6 is an example of a case with a low number of measurements.

### 6.3.1 Example 1: Uncontrolled Heating

The first example is a detached house with a water heater and the heating method is direct electric while the heating is classified as uncontrolled. The site has a significantly high percentage (83.3%) of heating adjusted to the optimal spot hours compared to other similar cases (see Table 2). The row index of the site is 36 in the heat map (Figure 9). The realised hourly cost comparison indicates that the load has been shifted from 22 and 23 hours into night hours, in addition to hour 7 seems to have more load in the optimised scenario (see Figures 9 and 12). The load disaggregation provides the maximum heating value of 3.8 kW and water heater rating 4 kW. The difference between the optimised and non-optimised scenario is 1.9% in total energy consumption and -3.7% in total cost. At the 2022 spot price, the difference in total cost is -10.6%.

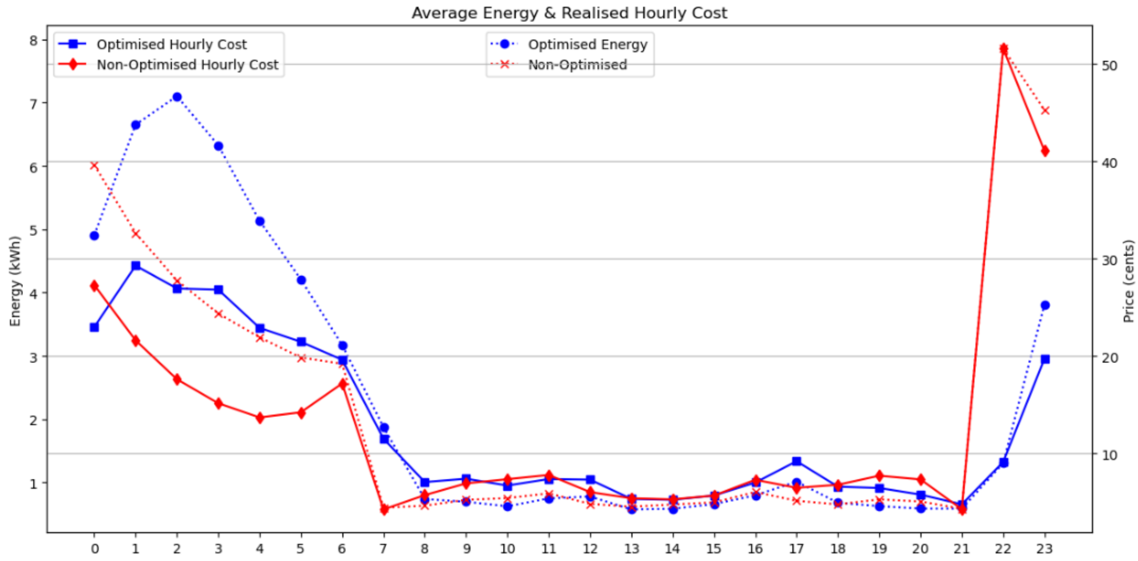


**Figure 12.** Hourly averages of energy and realised costs for example site 1.

Figure 12 indicates that although the heating of the site is classified as uncontrolled, the averages of energy are significantly higher during the hours 22 to 06, especially in the non-optimised scenario, as well as in the optimised scenario, but milder. This can be explained by the fact that the heating and water heater have a night electricity time setting and they are on only during this time. Therefore, this site is not a typical example of a case where the heating is classified as uncontrolled. The good result in the hourly cost comparison is due to the fact that the heating occurs during the night electricity period and these hours are on average the cheapest spot hours of the day.

In the non-optimised scenario, it is clear that loads are switched on in hour 22, whereas in the optimised scenario this phenomenon is mitigated. Furthermore, the lower energy averages in the optimised scenario compared to the non-optimised scenario during hours 22, 23 and 0 indicate that some optimisation of the loads has taken place. This can be assumed to be an optimisation of the operation of the water heater, since, as mentioned above, the heater is classified as uncontrolled. However, the disaggregation method is weak to determine the maximum heating power in such a case. Therefore, the statistics in Table 6 below do not fully explain the load transfer from 22 and 23 hours.

It is worth noting that there are only two hours of heating on at 7:00, while the comparison of realised costs indicates that there is more load in the optimised scenario. It is noteworthy that in this case the optimised scenario results in a 3.7% reduction in total costs, while the calculated total energy consumption increases by 2%.

**Table 6.** Statistics of the operating hours of the heating and water heater when the spot price is optimal, below the daily average of the sample site 1.

| Hour | 22:00 | 23:00 | 7:00 |
|---|---|---|---|
| Heating on & Spot Price Below Daily Mean | 63.4% | 74.7% | 0 |
| Water Heater on & Spot Price Below Daily Mean | 70.2% | 78.8% | - |
| Total Amount of Heating Operation Hours | 251 | 292 | 2 |
| Total Amount of Water Heater Operation Hours | 151 | 179 | - |
| Number of Measures | 365 | 365 | 365 |

### 6.3.2 Example 2: Good Total Cost in Optimised Scenario

The second sample is a detached house with a water heater and the heating method is direct electric heating. The site row index is 6 on the heat map in Figure 9. The load disaggregation provides the maximum heating value 3.9 kW and the water heater rating 2 kW. The difference between the optimised and the non-optimised scenario is 0.9% in total energy consumption and -2.1% in total cost. For the 2022 spot price, the difference in total cost is -6.9%. This site is used as an example because it has a slightly good result in total costs and to investigate the reason for the relatively high value of realised costs in hour 7 (see Fig. 9 and 13).

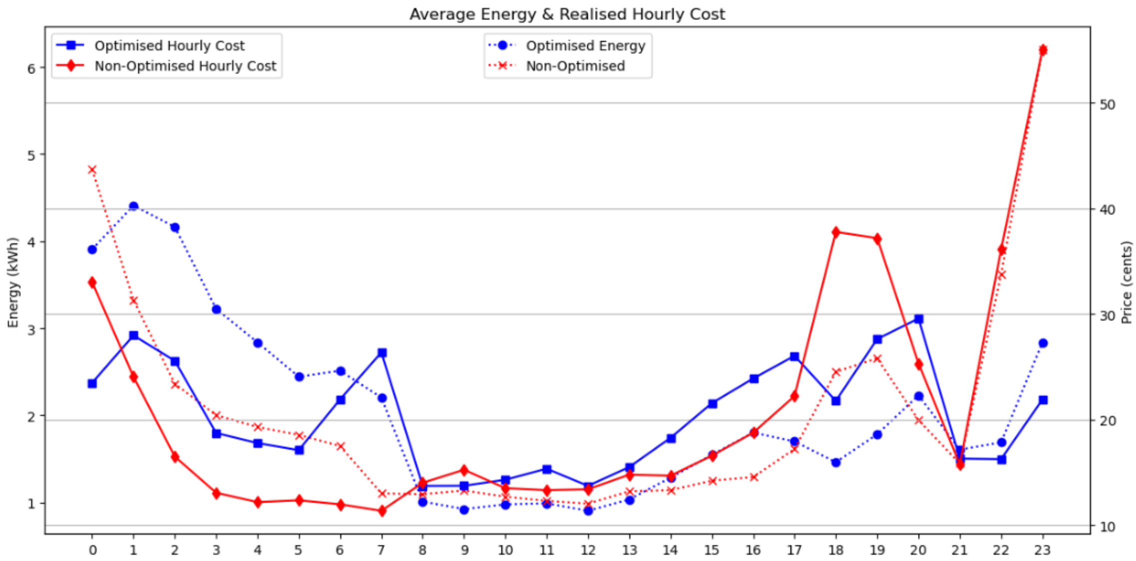


**Figure 13.** Hourly averages of energy and realised costs for example site 2.

The difference between optimised and non-optimised is at hours 22, 23 and 0, where the difference in realised costs is significant in favour of the optimised scenario. In the small hours, and in particular in hour 7, there is more load and therefore more realised costs with the optimised scenario. Here the difference in the cost profiles can be seen as a result of the optimisation. The increased load at hour 7 cannot be explained by load disaggregation, as the method does not find any heating hours (Table 7). The difference is explained, for example, by the fact that the water heater was only partially on, which can be the case if the water heater is configured to ensure that hot water is available in the morning.

**Table 7.** Statistics of the operating hours of the heating and water heater when the spot price is optimal, below the daily average of the sample site 2.

| Hour | 22:00 | 23:00 | 7:00 |
|---|---|---|---|
| Heating on & Spot Price Below Daily Mean | 60.0 % | 81.8 % | 100 % |
| Water Heater on & Spot Price Below Daily Mean | 55.6 % | 74.5 % | - |
| Total Amount of Heating Operation Hours | 85 | 77 | 1 |
| Total Amount of Water Heater Operation Hours | 108 | 98 | - |
| Number of Measures | 185 | 185 | 183 |

At hour 22, the difference in average hourly energy is 3.5 kW – 1.7 kW = 1.8 kW. Assuming that in the non-optimised scenario the water heater is always on at hour 22, the impact of the missing hours on the average of hourly energy can be approximated as follows. Based on the load disaggregation, the power of the water heater is 2 kW, and the number of hours the water heater is off is 185 h – 108 h = 77 h. The missing hours are multiplied by the power rating of the water heater divided by the total number of hours: (2 kW * 77 h) / 185 h = 0.8 kW. The effect of shifting of the heating load is difficult to estimate since the need for heating varies depending on the temperature. However, some of the remaining difference (1.8 kW – 0.8kW = 1 kW) can be assumed to due to optimisation of the heating.

### 6.3.3 Example 3: High Total Energy and Cost in the Optimised Scenario

The third sample is a detached house with a water heater and the heating method is direct electric. The row index of the site is 32 in the heat map (Figure 9). The load disaggregation provides the maximum heating value 7.3 kW and water heater rating 3 kW. The difference between the optimised and non-optimised scenario is 23% in total energy consumption and 34% in total cost. In the case of the spot price of 2022, the difference in the total cost is 18.4%.

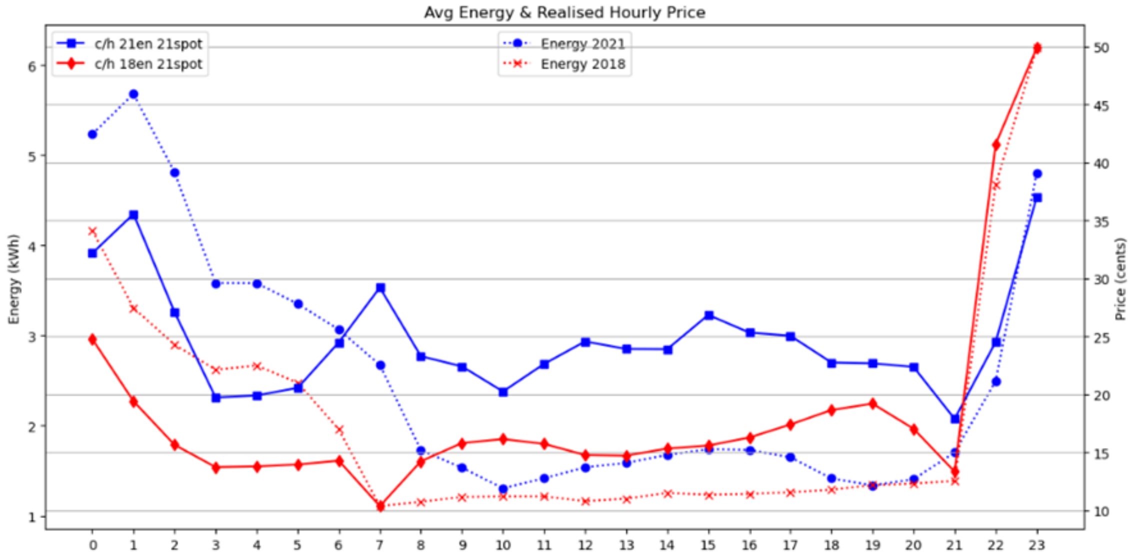


**Figure 14.** Hourly averages of energy and realised costs for example site 3.

As can be seen in Figure 14, the average energy and realised costs of the scenarios have the same shape and are consistently higher for the optimised scenario, except for hours 22 and 23. It is obvious that the total energy demand is higher in 2021 in the optimised scenario, and the reasons for this can only be assumed. As there is no information on whether behavioural or other characteristics affecting energy demand have changed between years, it can be assumed that, for example, heating energy demand has increased. However, as some load shifting is visible, the optimisation has managed to mitigate the cost impact by shifting some load from late evening to night hours. In addition, the cost impact of hour 7 in the optimised scenario can also be seen here.

The percentages for heating and water heating at hour 22 are relatively low (Table 8). The inability of the method to find the heating load at hour 7 also applies here. The average energy at hours 22 and 23 could be explained by the lower number of operating hours of the water heater. The disaggregated heating value is relatively high and therefore the number of operating hours in these sample hours is low compared to previous samples.

**Table 8.** Statistics of the operating hours of the heating and water heater when the spot price is optimal, below the daily average of the sample site 3.

| Hour | 22:00 | 23:00 | 7:00 |
|---|---|---|---|
| Heating on & Spot Price Below Daily Mean | 55.8 % | 69.8 % | 100 % |
| Water Heater on & Spot Price Below Daily Mean | 58.6 % | 77.0 % | - |
| Total Amount of Heating Operation Hours | 77 | 63 | 3 |
| Total Amount of Water Heater Operation Hours | 121 | 113 | - |
| Number of Measures | 235 | 235 | 234 |

### 6.3.4 Example 4: Higher Total Energy in the Optimised Scenario

The fourth sample is a detached house with a water heater and the heating method is direct electric. The site row index is 35 in the heatmap (Figure 9). The load distribution gives a maximum heating value of 6.2 kW and a water heater power of 5 kW. The difference between the optimised and non-optimised scenario is 36.1% in total energy consumption and 28.8% in total cost. In case of 2022 spot price, the difference in total cost is 22.5%. As can be seen in Figure 15 and compared to the previous example, this load profile is different, although in both cases the total costs and energy of the optimised scenario have increased accordingly. It is worth noting that in this case the non-optimised profile does not follow the night-time electricity routine where the highest loads occur after hour 22, instead the load is high and stable during the day and low at night.

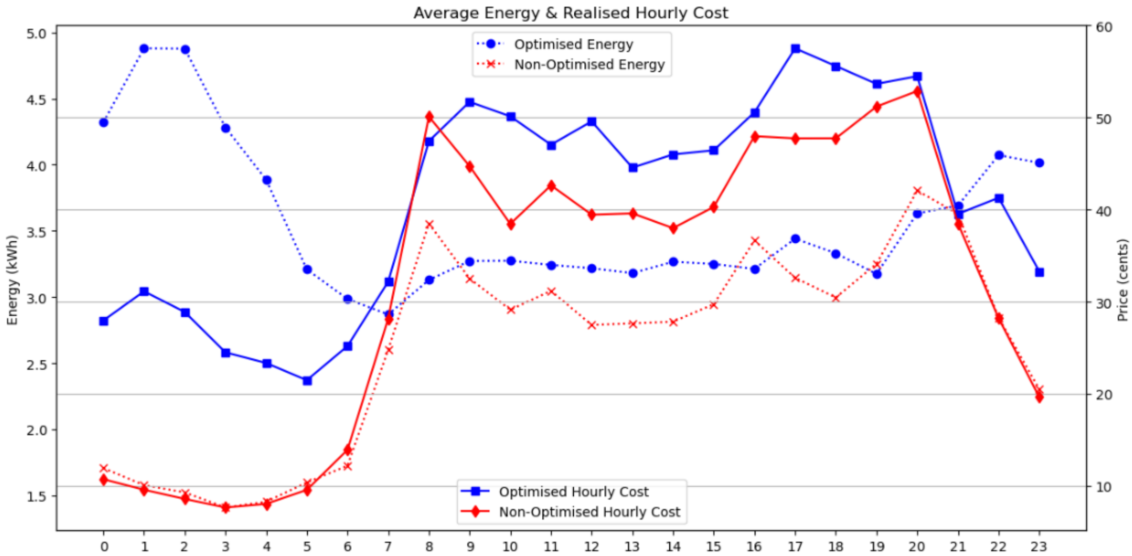


**Figure 15.** Hourly averages of energy and realised cost of sample 4.

The energy and cost lines are quite similar in shape and average during the hours from 7 to 21 (Figure 15), while in the late evening and early hours both energy and realised costs are significantly higher in the optimised scenario. This can be interpreted as a load shift caused by the optimisation. It is based on the assumption that the energy demand in 2021 is higher for unknown reasons, and that the optimisation has succeeded in shifting the load to the cheap small hours. The disaggregation statistics show that here too (Table 9), as in Example 3, when the estimated load is high, the number of operating hours is low. Hour 20 is chosen as an example hour to examine how heating disaggregation works when energy consumption is high during expensive spot hours. It can be assumed that the rather weak result of matching the heating hour to the optimal spot hour can be explained by the weakness of the method of disaggregating the heating load from the evening hour when the site normally has a high energy consumption.

**Table 9.** Statistics of the operating hours of the heating and water heater when the spot price is optimal, below the daily average of the sample site 4.

| Hour | 22:00 | 23:00 | 20:00 |
|---|---|---|---|
| Heating on & Spot Price Below Daily Mean | 51.4 % | 80.7 % | 30.3 % |
| Water Heater on & Spot Price Below Daily Mean | 58.1 % | 72.6 % | - |
| Total Amount of Heating Operation Hours | 37 | 31 | 33 |
| Total Amount of Water Heater Operation Hours | 43 | 51 | - |
| Number of Measures | 185 | 185 | 185 |

### 6.3.5 Example 5: Energy Storage as the Heating Method

The fifth sample is a detached house where the heating method is energy storage, and the site does not have a separate water heater for domestic water. The row index of the site is 38 in the heatmap (Figure 9). The load disaggregation provides as the maximum heating value 4.9 kW. The difference between the optimised and non-optimised scenario is -0.2% in total energy consumption and -2.1% in total cost. In case of 2022 spot price, the difference in total cost is -10.4%.

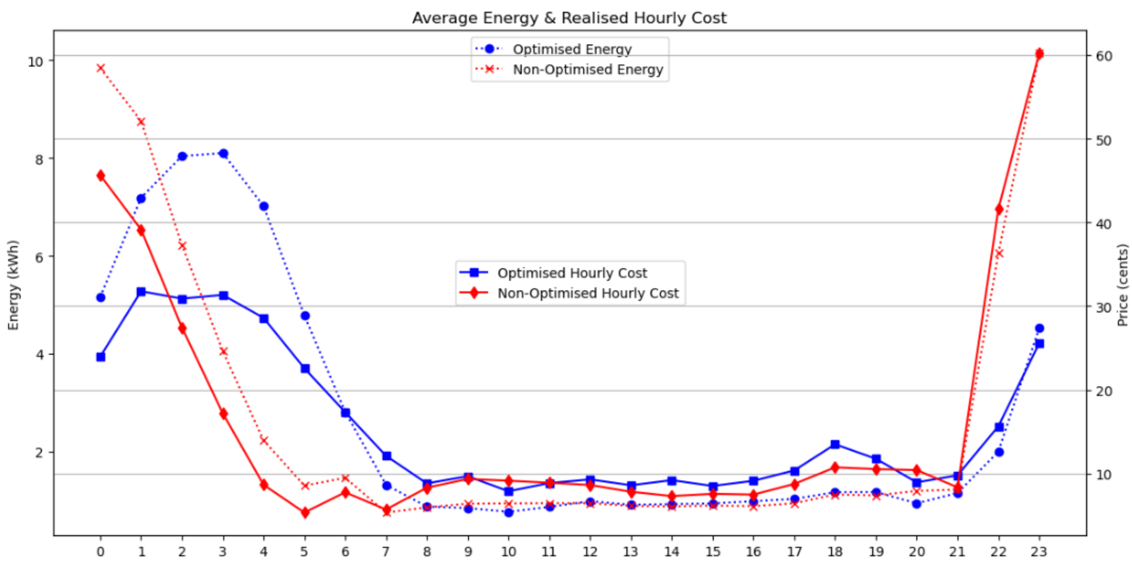


**Figure 16.** Hourly averages of energy and realised cost of sample 5.

In the non-optimised scenario, the heavy load has been on at 22 and a few hours forward (see Figure 16). These high values in energy and cost have been smoothed and damped by shifting the load into small hours in the optimised scenario.

**Table 10.** Statistics of the operating hours of the heating when the spot price is optimal, below the daily average of the sample site 5.

| Hour | 22:00 | 23:00 | 7:00 |
|---|---|---|---|
| Heating on & Spot Price Below Daily Mean | 63.0 % | 75.4 % | 100.0 % |
| Total Amount of Heating Operation Hours | 243 | 281 | 6 |
| Number of Measures | 364 | 364 | 363 |

In the case of no water heater, energy peaks are interpreted as heating loads, resulting in a high number of heating hours (Table 10). As it is difficult to determine the base load and maximum load in this case, an exception had to be made when fitting the model. Instead of a three-segment regression curve, only two segments are used, as shown in Figure 18. The base load and the maximum load are determined at the break points of the line, which consists of almost the entire temperature range. In addition, Figure 17 shows a cloud of points at certain values of the y-axis which can be assumed to be the power steps of the heating system. It is clear that the defined heating power (4.9 kW) is significantly lower than the highest point clouds, which are roughly estimated at 13 kW, 11 kW and 8 kW. It can be assumed that the water energy storage system has power steps for operation, in addition to the system heating the domestic water. Therefore, even though the number of heating operating hours is high in hours 22 and 23, the average energy is significantly lower than in the non-optimised scenario, probably because the heating power has been reduced by the optimisation.

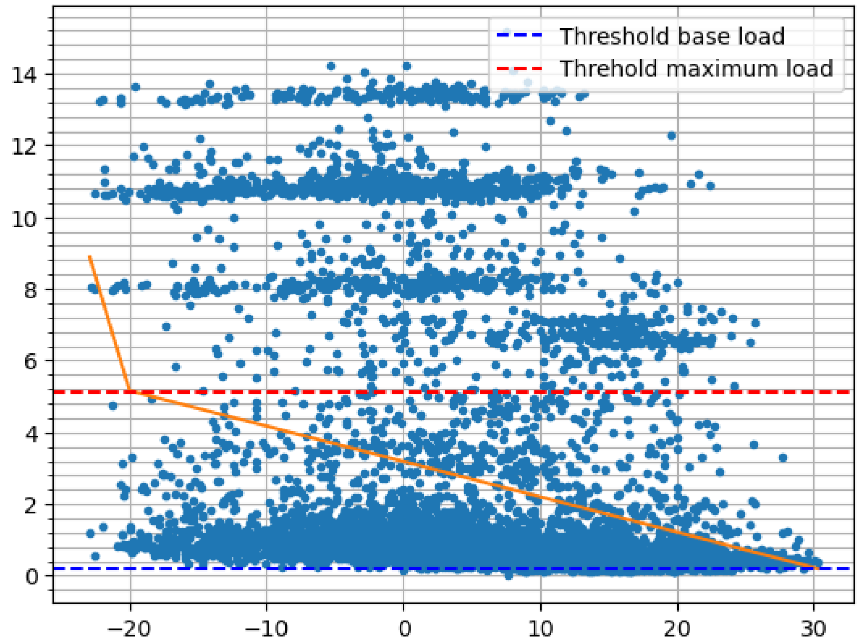


**Figure 17.** Heating load disaggregation in sample 5.

### 6.3.6 Example 6: Site with a Small Number of Measurements

The sixth and last sample is a detached house with a water heater and the heating method is direct electric. The site is presented as a sample with a small sample size on energy measures. The sites row index is 10 in the heatmap (Figure 9). The load disaggregation provides the maximum heating value 2.7 kW and water heater rating 2 kW. The difference of the optimised and non-optimised scenario in total energy consumption is 24,0 % and in total cost is 23,4 %. In case of spot price of 2022 is used for comparison, difference in total cost is 18,0%.

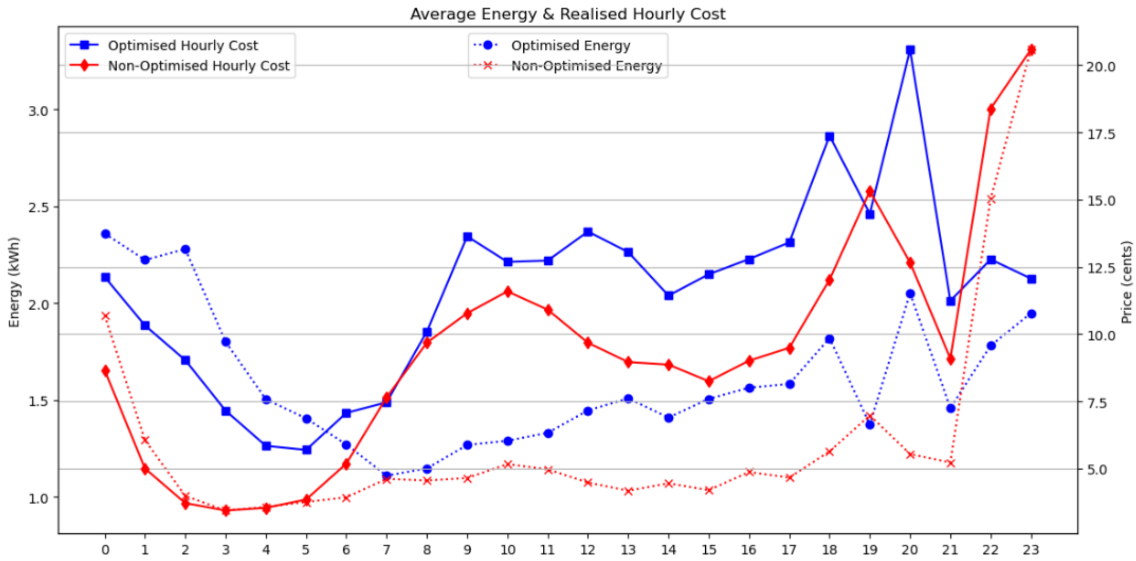


**Figure 18.** Hourly averages of energy and realised cost of sample 6.

In 2021, the optimised scenario, the average energy and the realised costs are all higher, except for hours 22 and 23 (Figure 18). During the day, even a small increase in energy has a large impact on the realised costs. Here too, the optimisation has had an effect and part of the load has shifted to the night hours from the late evening. Disaggregating the heating output is difficult in cases where there are a few measures from cold days. Therefore, the estimated heating output is low and the comparison of the heating operation with the optimal spot hours gives weak results, as can be seen in Table 11. Hour 19 is taken as the example hour as its average hourly cost is the highest. As can be seen in Table 11, only one out of 26 heating operating hours corresponds to the optimal spot hour. This highlights the reason for the weak overall results in cases like this.

**Table 11.** Statistics of the operating hours of the heating and water heater when the spot price is optimal, below the daily average of the sample site 6.

| Hour | 22:00 | 23:00 | 19:00 |
|---|---|---|---|
| Heating on & Spot Price Below Daily Mean | 48.9 % | 76.1 % | 3.9% |
| Water Heater on & Spot Price Below Daily Mean | 58.1 % | 72.6 % | - |
| Total Amount of Heating Operation Hours | 47 | 46 | 26 |
| Total Amount of Water Heater Operation Hours | 24 | 24 | - |
| Number of Measures | 122 | 123 | 122 |

# 7 Discussion

The aim of the thesis is to study how spot price-based optimisation has performed in a smart home pilot. The study consists of two tasks, the first task is to disaggregate the optimised loads from energy measures and compare how their operating hours match with optimal spot hours, and the second task is to compare optimised and non-optimised load profiles. The study also aims to identify which loads and sites are suitable for optimisation.

According to the results, there is a difference in the total energy consumption in the years 2021 and 2018. In general, the total energy consumption is higher in 2021 than in 2018, although there are cases where the total energy consumption is lower. However, without information on behavioural, social, and other characteristics of households that could explain the differences in consumption or provide perspective on the impact of these characteristics on energy demand between the years. It is reasonable to assume that, for example, the need for heating energy may have increased. Furthermore, even with similar cases, loads and metadata, the results show a large variation in the difference in energy consumption between the optimised and non-optimised scenario. It is thus difficult to produce strictly factual, generalised, and scalable results of the optimisation.

## 7.1 Task 1: Disaggregated Loads

Heating disaggregation worked for households without hot water heaters because the energy peaks were noticeable and could be interpreted as heating energy. Therefore, the best results of heating operating hours compared to optimal spot hours were for sites with heat pump, water energy storage and district heating as heating method. As the number of these sites is only four included in this study, it is inappropriate to draw a direct relationship that these types of heating methods are suitable as optimised loads based on the results. However, such notations can be found in the literature, Suhonen et al. (2020) claim that dynamic pricing of district heating significantly affects the potential savings from demand response strategies. In addition, both Claußet al. (2019) and Hirvonen et al. (2020) argue that heat pumps in direct electric heating systems have the potential to reduce the peak demand for heating energy. Sites with the most typical method of heating in the pilot, direct electric heating, have varying degrees of heating operating hours compared to optimal spot hours, the best sites have their percentage close to 80%, while the average is 61%. The percentage for all sites is 62%.

Households with a low number of measurements have difficulties in estimating the maximum heating output, especially if cold data are missing. In this case, the assumed heating power remains low, which makes disaggregation difficult. In addition, load disaggregation is a challenge for households with oil burners, as their energy-temperature regression curve decreases at low temperatures, indicating that an oil burner is in use. In cases where the heating is not controlled, the disaggregation of the heating load is challenging because the method used captures the maximum heating output and not the hours when the heating is only partially on. Furthermore, in the case of high energy consumption in the evening, when the spot price is higher on average, the load disaggregation results are questionable, as it is not certain whether the heating is truly on during the recorded hours.

The values of water heating operating hours compared to optimal spot hours are relatively close to the hourly reference percentage. However, the weakest results are significantly low, indicating that the method used is not applicable in these cases. The simple statistical algorithm and method used in this research was not able to find all the water heater operating hours. In addition, the simplifications of the method only allow for a rough estimation and present a challenge in data analysis. However, the iteration of the water heater rating for each site provided credible results.

Defining heating and water heater operating hours at optimal spot price is challenging when there is no certainty that the disaggregation model works. The main challenge in this task is the separation of the water heating load from the heating load. The percentages of how the load operating hours are matched to the optimal spot hours vary a lot, as the best percentages are around 80%, which can be considered as a good result, while the lowest ones indicate serious problems with the suitability of the model for certain cases. Related studies, which could be used to develop more advanced disaggregated models, are presented in Section 7.4.

## 7.2 Task 2: Comparing Load Profiles

The results show that demand response is efficient in shifting the load from hours 22 and 23 to the night hours 1 to 5, which consequently has an impact on the energy costs for the customers. Despite an overall increase in total energy consumption in the optimised scenario, this load shifting mitigates the cost impact. Therefore, the performance of the optimisation can be considered successful. When the optimised and non-optimised scenarios are calculated based on the 2022 spot price, the cost difference is generally in favour of the optimised scenario. This may be due to the more volatile 2022 spot prices. However, comparing scenarios in different spot prices is problematic because loads are optimised to correlate with real day-ahead prices of 2021. Better results for total costs in 2022 spot prices suggest that the cost difference is due to greater variation in the total between hours, i.e. when the load is shifted from late evening to the early hours of the night.

In several cases, the increase in load in the optimised scenario at hour 7 cannot be explained by load disaggregation because the method does not identify heating hours. For example, the difference is explained by the fact that the water heater was only partially on; this may be the case if the water heater setting is configured to ensure hot water availability in the morning. The disaggregation method used in this study only takes into account the maximum heating output, so it is not possible to record the hours when the heating is only partially on.

The monthly load profile comparison shows that the percentage value of the profiles is negative for the scenarios, indicating that electricity is consumed when the price is below the monthly average. The optimised scenario has slightly lower values compared to the non-optimised, but in November and December the non-optimised profiles are more successful. A different curve in November-December may be due to a higher demand for heating energy. The relatively good overall values for the non-optimised profiles can be explained by the fact that energy consumption at many sites follows the night-time electricity routine, where heating and/or hot water are set to operate during the late evening and night hours, which are typically the cheapest spot hours of the day.

As described by Motiva (2024), the temperature-dependent energy consumption of the house can be compared between two years using Heating Degree Day (HDD) values. The comparison between years is made by normalising the heating energy consumption with the HDD values of the corresponding period. While it was not possible in this study to reliably disaggregate the temperature-dependent heating energy and the energy required for water heating, the monthly HDD values for Vaasa can be observed, as shown in Table 12. For November and December, the heating degree day value is higher in 2021 compared to 2018, i.e. optimised and non-optimised scenarios in the case study. Although it is not possible to calculate the exact effect, it can be assumed that the demand for heating energy in these months is higher in the optimised scenario. This could explain part of the difference in November and December in the monthly comparison of load profiles.

**Table 12.** Heating degree days of Vaasa in 2021 and 2018 (FMI, 2024b).

| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 696 | 716 | 559 | 425 | 235 | 0 | 0 | 21 | 226 | 306 | 525 | 760 | 4469 |
| 2018 | 650 | 731 | 713 | 416 | 50 | 15 | 0 | 0 | 114 | 354 | 420 | 588 | 4051 |

## 7.3 Limitations of This Study

This research has several limitations and challenges that affect the interpretation of the results. A major limitation is the lack of metadata detailing specific characteristics of the households, such as insulation quality, age, size and number of occupants. In addition, there is no information on consumption habits or any knowledge of what has happened to the household appliances and equipment over time. It would have been beneficial for this research to have known the customer profiles and historical data on their past performance. Furthermore, the classification of 'uncontrolled heating' in the metadata is not clear. Clearly, in some cases it is controlled by the night-time electricity setting, with relays on at 22, and in some cases it is controlled by thermostats. In addition, the metadata does not specify whether additional heating sources are used at the sites.

The hourly sampling rate of the measurements is considered to be very low, and future measurements with a 15-minute interval may facilitate a more accurate load disaggregation as in this study. It is important to note that the optimisation is done for 2021 hourly spot prices, therefore the comparison results of scenarios based on 2022 spot prices are only theoretical. In the results, the optimised and non-optimised scenarios usually differ during the hours 22, 23 and 0. The load shift to the night hours highlights the difference in the more variable spot price of the year 2022 between the early evening hours and the small hours.

## 7.4 Suggestions for Further Study

In order to address the issue of water heater disaggregation, and additionally the issue of heating disaggregation, a model based on machine learning could be developed using test and training data with labelled 'device is on' information. This would improve the accuracy of load disaggregation and overcome the limitations of the methods used in this study.

In their study on disaggregating water heaters from household electricity data, Bongungu et al. (2022) state that their algorithm requires a training period where water heater operation is prominent to derive accurate disaggregation parameters. Furthermore, they claim that the performance of the algorithm is affected by the resolution of the input data, with longer periods, such as 30 minutes, leading to higher error rates in distinguishing electricity consumption from other appliances. The study by Belikov et al. (2022) constructed an unsupervised model for disaggregating water heater consumption and evaluated its effectiveness using a labelled dataset. Their approach was based on the understanding that water heaters are typically programmed to operate only during off-peak hours. Pardiñas et al (2023) concludes that non-intrusive and low-cost techniques to accurately measure consumption are essential for the success of water heater optimisation.

The method proposed by Eskander & Silva (2021) is a hybrid approach combining statistical data with clustering and behavioural prediction to disaggregate household electricity consumption. The method is validated using a dataset with a 10-minute sample rate, including total consumption and specific household appliances. Holweger et al. (2019) devise a hybrid approach that integrates inputs from a standard time-of-use study, household load profiles obtained from smart meters, and specific household characteristics collected through a study. The algorithm aims to identify which appliances are used at certain times of the day by understanding the characteristics of the household and the likelihood of certain activities occurring at different times. The method estimates the power signals of appliance categories grouped by their likelihood of use and is suitable for very low sampling rates.

In conclusion, validating a model with a labelled dataset is crucial for non-intrusive load monitoring disaggregation. Conducting surveys on household behaviour or consumption habits provides the basis for modelling. In addition, a study that focuses on a specific time period, rather than the entire measurement period or a specific type of site, would provide more accurate results on how different cases and loads are suitable as optimised loads.

# 8 Conclusion

The focus of this study is on demand response in the residential sector and its potential benefits for both electricity consumers and utilities. The aim of the study is to analyse measured energy data from smart home pilot sites to address two main research questions. Firstly, it investigates the performance of spot price-based optimisation in minimising electricity costs for customers. This is done in two tasks, by examining the operating hours of optimised loads, heating and water heating, at optimal spot prices, and by comparing optimised and non-optimised load profiles. Secondly, the impact of different smart home pilot loads on customer load profiles is estimated to determine their suitability for optimisation.

Heating disaggregation is effective for households without hot water heaters. In these cases, heating hours are well matched to optimal spot prices. Sites with the most typical method of heating in the pilot, direct electric heating, have varying degrees of heating operating hours compared to optimal spot hours. The comparison of load profiles showed the effectiveness of demand response in shifting load from evening to night hours. In addition, the results showed that, on average, electricity is consumed in the pilot when the price is lower than the monthly average. The results showed differences in total energy consumption between the optimised and non-optimised scenarios, with overall higher consumption in the optimised pilot year. However, without detailed information on household characteristics, it is not possible to explain these differences in this study.

Challenges to the study include a lack of detailed household metadata and characteristics, large variations in energy consumption between scenarios, and low numbers of measures in some sites. Furthermore, disaggregating the energy measure into heating load and water heater posed challenges. Generalising findings is therefore difficult. Developing machine learning based models to disaggregate load and exploring hybrid approaches that integrate statistical data with behavioural prediction are possible solutions to increase the accuracy of estimating the performance of the optimisation. Validating models with labelled datasets and understanding household behaviour is critical for accurate non-intrusive load monitoring disaggregation. Conducting surveys to collect detailed household information can improve the accuracy of modelling and provide insights for optimisation strategies.

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